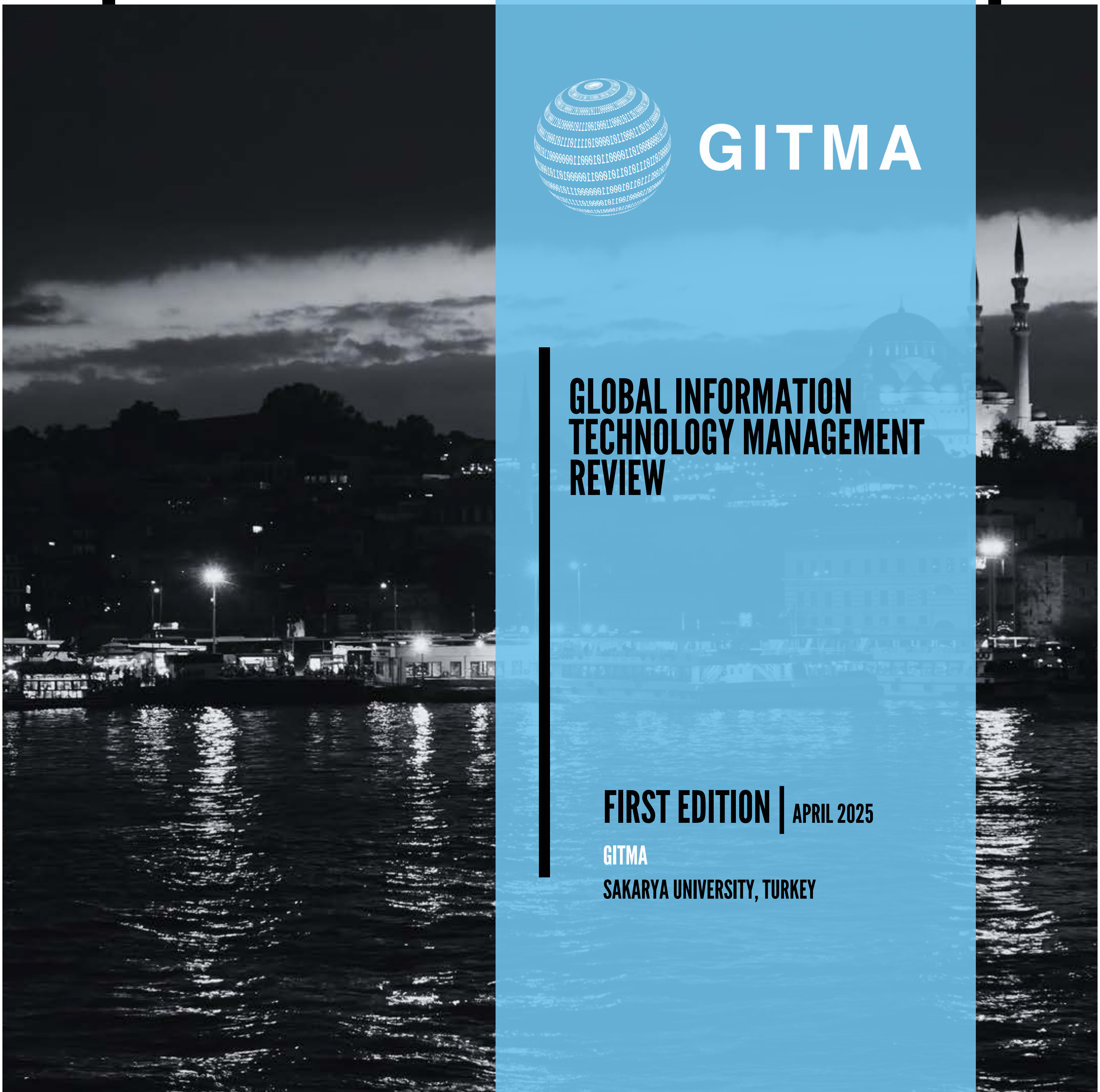


GITMA

GLOBAL INFORMATION TECHNOLOGY MANAGEMENT REVIEW

FIRST EDITION | APRIL 2025

GITMA

SAKARYA UNIVERSITY, TURKEY

https://gitma.org/

Revista de Investigación, Año 1, núm 001- abril 2025, es una publicación anual editada por K5 Services, S.A. de C.V. para GITMA Global Information Technology Management World, con domicilio en Cruz Manca, Prolongación Paseo de la Reforma No. 1190 Torre B, Piso 21, Col. Cruz Manca, Alcaldía Cuajimalpa de Morelos, C.P. 05349, Ciudad de México, México. Teléfono: 55 5081 2070.

Página electrónica: https://www.gitma.org/gitma-2026
Correo electrónico: legal@ndscognitivelabs.com.

Editor responsable: Gustavo Ricardo Parés Arce.
Certificado de Reserva de Derechos al Uso Exclusivo No. 04-2026-020614152500-102 e ISSN: en trámite, ambos otorgados por el Instituto Nacional del Derecho de Autor.
Responsable de la última actualización de este número: Gustavo Rivcardo Parés Arce, con domicilio señalado ante-
riormente.

Fecha de última modificación: 15 de diciembre de 2025.
Tamaño del archivo: 10.3 MB.

GITMA

GUSTAVO
PARÉS

CONFERENCE CHAIR

Message from Conference Chair:

It's an honor for me to be here at Sakarya University in Türkiye on our 22nd GITMA Annual Conference. In recent years, with the acceleration of technology adoption and new breakthroughs in Artificial Intelligence and Large Language Models, it has become more important to spend time building a network of research, academia, and industry practitioners to learn, comment, and build the new world we will live in, surrounded by technology.

As I have witnessed both in academia and the business world how global IT is reshaping the world in all relevant aspects of life, starting with education and how we do research, today is difficult to entertain yourself without wifi or a digital device music, news, books, movies and all kind of activities depend on global IT infrastructures and technology teams working together across the globe.
Please take the time over the next couple of days to talk with each other and listen to what is happening in other areas of research, other countries, and with other cultures. Many papers, friends, and other collaborations have started from events like this today.

I am grateful to all our GITMA team and all its members for making this event happen, as well as the local authorities in Sakarya University and its faculty and staff for working last month to coordinate this event.

GITMA

AYKUT H. TURAN

LOCAL CHAIR

Message from Local Chair:

Welcome to Sakarya, with over 1 million people in total, conveniently located in the Marmara region of Turkey. Sakarya is in the Northwest part of Turkey, about 110 km east of Istanbul. Sakarya University is located in the western part of the province and within 20 minutes' driving distance of the downtown area.

Regarding population, Sakarya is the 20th populous province in Turkey and the 5th populous city in the Marmara region. The name Sakarya comes from the long river that divides the province into two parts, from North to South. Sakarya has a long history dating back to Frigs area After Frigs, Sakarya occupied by Lydians and later Persians. Many international companies are headquartered in Sakarya, for example, Toyota Motor Company Europe, Coca-Cola Company, Daikin Heating and Air Conditioning, Goodyear Tires, Yazaki Otomotive, Toyota Boshoku Turkey, and other large companies.

Sakarya is unfortunately located on the northern Anatolia fault plate, so it is an extremely earthquake-prone region. In 1999, the big Gölcük Earthquake killed more than 50,000 people in the area. Hence, we have a vital Earthquake Museum downtown.

Islam köfte are traditional Turkish meatballs originating from Adapazarı, the capital of Sakarya province. The meatballs are usually made with grated stale bread, ground beef, onions, garlic, cumin, paprika, eggs, salt, and pepper. They are a traditional meal in Sakarya. Soup and pumpkin sweets are also very famous and traditional meals in Sakarya.

I hope you will enjoy our Acarlar Longozu trio on Tuesday afternoon. All of you are welcome to join. Acarlar Floodplain Forest (Turkish: Acarlar Gölü Longozu) is a floodplain forest in Sakarya Province, northwestern Turkey. It is a combination of seaside, lagoon, dunes, and forest. At a distance of 2 km (1.2 mi) from the Black Sea, the floodplain forest stretches over 12 km (7.5 mi) in length and a width of 1.0–1.5 km (0.62–0.93 mi).

It has been a great effort and intensive teamwork to prepare this year's GITMA Conference. I especially would like to thank Gustavo Peres, Prashant Palvia, Natalia Oliguin, Halil Ibrahim Cebeci, and Hajer Kefi as our core team.

I would like to extend my special thanks to the administrative and academic staff of Sakarya University for their valuable support and guidance.
Thank You

DR. PRASHANT PALVIA

HONORARY PRESIDENT AND ADVISOR

Message from Honorary Chair

Dear friends and colleagues:

Twenty-five years ago! That's right. It was 25 years ago when the first conference of the Global Information Technology Management Association (GITMA) was held In Memphis, Tennessee, USA in June 2000. Several of us launched the conference with a clear conviction and vision that we needed to bring the IS/IT academicians and researchers from all over the world together once a year to share their insights and experiences. That conviction and vision holds even today with greater purpose and clarity. Together, we held the GITMA conferences all over the world including Memphis, Dallas, New York, Calgary (Canada), San Diego, Anchorage (Alaska), Orlando, Naples (Italy), Atalanta, Mexico City, Washington, D.C., Las Vegas, Bangalore (India), Kuala Lumpur (Malaysia), Philadelphia, St. Louis, San Diego, Mexico City, Paris (virtual), Mexico City, and Boston (Virtual). Along the way, we made remarkable achievements, made lifelong friends, and had great fun while doing all of that.

While I was the conference chair and President of GITMA for the first 18 years, I handed over its leadership to Mr. Gustave Pares in the year 2019, and now serve as an advisor to the association. We met Gustavo in the 2007 conference in Naples, Italy when he was a recently minted MBA graduate and was looking to discover his own path in the IS field. He offered to host the conference in 2009 in Mexico and subsequently held many more conferences. Gustavo went on to become a successful international entrepreneur in IT and is currently the CEO of several companies in Mexico. This year again, Gustavo is the Conference Chair,

In my role as the Founder and Advisor for GITMA, I am pleased to welcome you all to the GITMA-2025 conference being held at Sakarya University in Sakarya, Turkey. The Local Chair for the conference is Professor Aykut Turan, who I have known for more than a decade and have developed a close friendship. The Program Chairs for the conference are Prof. Hajer Kefi of France and Prof. Halil Ibrahim of Turkey. Gustavo, Aykut, Hajer, and Halil have all worked tirelessly over the past year to bring you an excellent program. They were assisted by many staff members at NDS Cognitive Labs, most particularly Ms. Natalia Olguin. My sincere thanks to all of them.

The conference committee has prepared an excellent program. There are several paper sessions, panels and workshops at the conference. At any given time, you can find something of interest to you that will enhance your professional career. Besides being a great educational opportunity, the GITMA conference has always been a great socializing and networking experience. Given the smallness and coziness of our group, you can practically meet everyone and develop research and professional alliances that can last a lifetime. On that note, please be sure to participate in the many social events that have been carefully organized by the conference committee.

I wish you the best. Enjoy the conference and come back to future conferences.

Sincerely,

Prashant Palvia, Ph.D.
Founder and Advisor, GITMA
Emeritus Professor and Past Joe Rosenthal Excellence Professor
The University of North Carolina Greensboro, USA

GITMA

PREFACE

The 22nd Annual Global Information Technology Management Association (GITMA) Conference provides a global platform for scholars, practitioners, and industry leaders to engage in meaningful dialogue on the transformative impact of technology on business and society. Held in Sakarya, Turkey, GITMA 2025 emphasizes innovation, collaboration, and knowledge sharing across borders. This year's conference highlights critical themes, including artificial intelligence, digital transformation, blockchain, data analytics, and the global digital workforce. By bridging academic research with industry application, GITMA fosters interdisciplinary conversations that address real-world challenges and opportunities in the digital age. The conference aims to cultivate new partnerships, showcase cutting-edge research, and promote inclusive and sustainable technology practices. As digital ecosystems continue to evolve, GITMA remains committed to advancing thought leadership and practical solutions that have a meaningful impact at both local and international levels. Together, we shape the future of global IT management through collaboration, insight, and shared purpose.

ACKNOWLEDGMENTS

The success of the 22nd Annual Global Information Technology Management Association (GITMA) Conference would not have been possible without the dedication and hard work of many individuals. We extend our sincere gratitude to Natalia Olguin, who served as the Organizing Committee Chair and played a pivotal role in coordinating all aspects of the conference with exceptional professionalism and care.

We are also deeply thankful to our Session Chairs for their invaluable contributions in reviewing papers, guiding discussions, and ensuring the academic quality of each session. Their efforts were central to the success of GITMA 2025.

Session Chairs:

A. Kadir Hızıroğlu
Aykut Hamit Turan
Ayşegül Aydın
Büşra Alma Çallı
Berrin Denizhan
Emrah Aydemir
Hajer Kefi
Gustavo Parés
Prashant Palvia
Tim Jacks

To all participants, speakers, authors, and volunteers — thank you for making GITMA 2025 a truly global and collaborative event.

GITMA

CONFERENCE SCHEDULE

June 2, 2025

Time	Activity
8:30 - 9:00	Registration
9:00 - 9:30	Welcome Address – Gustavo Parés (GITMA President)/ Rector/ vicerrector
9:30 - 10:15	Academic Keynote – Shirish C. Srivastava
10:15 - 10:45	Coffee Break
10:45 - 12:15	Simultaneous Sessions & Panel: Publishing in IS Journals – Palvia, Dwivedi, & Jacks.
12:15 - 13:30	Lunch
13:30 - 15:00	Simultaneous Sessions & Workshop: Data Analytics for IT Management – Florin Grigorescu
15:00 - 15:30	Coffee Break
15:30 - 17:00	Simultaneous Sessions & Workshop: Navigating in the Digital Age – Gülseçen, Derndere.
17:00 - 18:30	Open Session / Flex Time
19:00 - 20:30	Conference Reception

GITMA

CONFERENCE SCHEDULE

June 3, 2025.

Time	Activity
8:30 - 9:00	Day 2 Check-in and Registration
9:00 - 10:30	Simultaneous Sessions & Workshop (Repeat): Navigating in the Digital Age – Gülseçen, Derndere
10:30 - 11:00	Coffee Break
11:00 - 12:30	Simultaneous Sessions
12:30 - 14:00	Lunch Break
14:00 - 18:00	Group Trip / Site Visit https://tr.wikipedia.org/wiki/Acarlar_Longozu

GITMA

CONFERENCE SCHEDULE

Juve 4, 2025.

Time	Activity
8:30 - 9:00	Day 3 Registration
9:00 - 10:00	The World IT Project- Prashant, Aykut, Tim
10:00 - 10:15	Coffee Break
10:15 - 10:45	Industry panel - Rahul Banerjee, Gustavo Pares, Tim
10:45 - 11:30	Closing Remarks – Gustavo Parés, Aykut, Halil & Hajer.

GITMA

ORGANIZING COMMITTEE

ORGANIZING COMMITTEE

The success of the 22nd Annual Global Information Technology Management Association (GITMA) Conference would not have been possible without the dedication, creativity, and tireless efforts of the Organizing Committee. This team worked behind the scenes for months to ensure a seamless and enriching experience for all participants. From program scheduling and paper reviews to on-site logistics, communications, and digital infrastructure, the Organizing Committee played a vital role in bringing the conference to life.

We extend our deepest gratitude to Natalia Olguin, who led the organizational efforts with remarkable professionalism and commitment. Her leadership in coordinating across teams, managing participant needs, and supporting both academic and practitioner communities was instrumental in the success of GITMA 2025.

We also thank the GITMA Board and all session chairs, reviewers, and contributors who collaborated to make this year's conference a space for global knowledge exchange and interdisciplinary dialogue.

Together, their work exemplifies the spirit of innovation, collaboration, and excellence that defines the GITMA community.

SPONSORS AND SUPPORTERS

NDS® NDS COGNITIVE LABS

KP KeyPrediction

Paper #5

Title: Artificial Intelligence in Military Decision-Making: Exploring the Normative and Strategic Implications

Author: Natalia Olguin Montemayor (UNU-MERIT, Maastricht University)

Abstract:
This paper explores how AI is reshaping military decision-making and examines the ethical and strategic risks it poses. It highlights concerns around human oversight, bias, and governance, calling for clear frameworks to ensure responsible use of AI in defense contexts.

Keywords: Artificial Intelligence, Military Strategy, Norms, Decision-Making, Ethics

Paper #14

Title: Ethical Implications of Artificial Intelligence in Healthcare: A Bibliometric Analysis and Systematic Review

Authors: Esra Dündar Aravacık, Güler Koştı and Serhat Burmaoğlu

Abstract:
This study examines the ethical challenges posed by AI in healthcare through a bibliometric and systematic review of 284 scholarly articles. It identifies key thematic areas such as human agency, bias, privacy, and stakeholder perspectives, highlighting the field's evolution from foundational ethics to practical implementation strategies.

Keywords: Artificial Intelligence, Healthcare Ethics, Machine Learning, Bioethics, Bibliometric Analysis, Systematic Review

Paper #15

Title: Revolutionizing Organizational Performance through AI Integration: A Systematic Review

Author(s): Ravi Seethamraju and Angela Hecimovic

Abstract:
This paper systematically reviews the recent literature to assess how the integration of artificial intelligence (AI) enhances organizational performance. Key findings highlight AI's role in boosting operational efficiency, innovation, and strategic agility, while also identifying challenges in implementation, workforce adaptation, and data governance.

Keywords: Artificial Intelligence, Organizational Performance, Digital Transformation, Systematic Review, Innovation

NAVIGATING AUTOMATION BIAS IN AUITING: EXPLORING ARTIFICIAL INTELLIGENCE IMPACT

INTRDOCUTION

AI is becoming an indispensable technology in business with investments in AI projected to reach $200 billion by 2025 (Goldman Sachs, 2023) and its deployment is increasing. According to a survey conducted by the Australian Financial Review, about 50% of the top 100 accounting firms in Australia are using AI-driven services in streamlining operations, automating repetitive tasks and providing better customer service, and growing at faster rate than others (AFR, 2024). A study by KPMG found that around 75% of Australian firms are adopting AI and looking to auditors to lead AI use in auditing and financial reporting (KPMG 2024). Their study also observed that AI is changing auditing, and bias and data privacy are the major concerns while uncertain ROI, staff worries about displacement, changing regulations and risk of using algorithms with no human oversight are the barriers for their adoption and use (KPMG 2024).

Although AI technologies have demonstrated their potential to enhance decision-making and improve worker productivity, significant concerns persist regarding the risks associated with their growing dominance (Koreff et al., 2023). These risks include automation bias in decision making. Automation bias refers to the human tendency to exert less cognitive effort when the technology tool replaces vigilant information seeking and processing (Skitka et al., 2000). Over time, such reduction in human vigilance may contribute to the potential loss of critical expertise in the organisations (PCAOB 2021; Sutton et al., 2023). When individuals overly rely on AI outputs without critical evaluation it may further amplify that bias (Tilbury and Flowerday, 2024) in their decision making. In professions such as auditing, this may lead to loss of essential expertise and critical thinking abilities, as auditors grow overly dependent on AI systems to perform tasks that traditionally require proactive involvement in the decision making processes and professional judgment (PCAOB, 2021; Sutton et al., 2023; Koreff et al., 2023).

Several scholars have emphasized the need for research to better understand how the firms are navigating the automation bias in auditing and their implications (Vitali and Giuliani, 2024; Samiolo et al., 2023; Suton et al., 2023; Murray et al., 2021). Theory of Technology Dominance (TTD) (Arnold and Sutton, 1998) and its extension (TTD2) that focused on the deleterious effects of technology dominance (Sutton et al., 2023) as our guiding framework, our study explores the automation bias, the most dominant effect of AI use. TTD and broader literature (Tilbury and Flowerday, 2024; Samiolo et al., 2023; Rinta-Kahila et al., 2023) theorises automation bias as one of the significant potential effects of technology use. Using a qualitative research methodology and semi-structured interviews as a data collection strategy, our study investigates these dynamics to better understand the phenomenon of automaton bias in auditing context. We analyse the interactive effects of three key elements – i) auditing environment – that includes the procedural and regulatory context; ii) technology – that refers to the systems that function in a restrictive way or collaborative way, mandatory or voluntary use, and with or without human intervention and supervision; and individuals (i.e. auditors) with varying levels of expertise.

By identifying and empirically analysing the potential effect of automation bias, our study aims to help audit firms, standard-setting bodies, professional organizations and clients to develop strategies to mitigate bias and maximize benefits of AI use in auditing. It can assist auditors in cultivating necessary skills and guide AI tool designers in creating systems that enhance human capabilities. Our findings will have significant implications for audit firms' strategies concerning AI deployment, audit methodologies, skill development, and the establishment of governance standards and regulations. Remainder of the paper starts with a brief review of relevant literature, followed by methodology, analysis and findings, and conclusions.

LITERATURE REVIEW

AI-enabled tools are expected to deliver significant improvements to auditing by transforming the traditional trade-offs between speed, cost, and quality (Almufadda and Almezeini, 2022). These tools excel in simultaneously managing multiple complex dimensions of information - space, time, and internal structure, while offering the intentionality to shape algorithms, protocols, selection of actions and decision-making processes (Murray et al., 2021). This increased reliance on AI, however, introduces a host of ethical, technical, legal, and organizational challenges (Dwivedi et al., 2021), leading to risks associated with technology dominance. These risks include automation bias, complacency, deskilling, and trust issues (Sutton et al., 2023; Arnold et al., 2023). Such dominance, it is argued, has the potential to fundamentally reshape the auditing profession, affecting its operations and professional identity (Susskind & Susskind, 2022; KPMG, 2024). With AI tools increasingly becoming more sophisticated and capable of mimicking auditor judgment and decision-making, and their use likely to become mandatory within audit firms (Boland et al., 2019; Dowling et al., 2018), understanding their impact and implications is critical.

Automation bias, a key effect of technology dominance, refers to the human tendency to exert less cognitive effort with technology replacing vigilant information seeking and processing (Malaescu and Sutton, 2015: Skitka et al., 2000). Akter et al (2021) identified three primacy sources of bias – data-related bias, methodological bias and society-driven bias. While data related bias includes issues such as underrepresentation in samples or inadequate data cleaning, methodological bias refers to problems such as spurious correlations or flawed algorithm selection and the society-driven bias is rooted in historical and institutional behaviour (Akter et al., 2021). Mehrabi et al. (2021) categorized various forms of bias and corresponding mitigation approaches, grouping them into interrelated components based on context, data, algorithm, and user interaction. The US National Institute of Standards and Technology (NIST) identified three main categories of AI bias that are deeply interconnected – systemic bias, computational bias and human bias (Schwartz et al., 2022). Systemic bias stems from beliefs or institutional norms that influence the design and development of AI systems (e.g. societal, historical or institutional factors), while computational bias results from data and methodological flaws that impact an AI artifact's performance (e.g., representation, feedback or label bias). The third category, human bias refers to human perceptions and heuristics that impact the use of an AI tool (e.g. deployment, anchoring, availability or confirmation bias) (Schwartz et al., 2022).

Divergent ideals, beliefs, and practices among those involved in the design and development of AI artifacts can inadvertently lead to the neglect or overemphasis of critical elements, potentially contributing to bias and affect accuracy and fairness of outcomes. Additionally, the specific tasks to which AI is applied play a significant role in shaping how bias is defined and identified (Kordzadeh and Ghasemaghaei, 2022). AI tools operate through 'formal' rationality that involves quantitative calculations, rigid rule sets and mathematical optimization procedures. Formal rationality embedded in AI algorithms influences not only the use of data, but also the data creation processes (Nishant et al., 2024). Such AI algorithms have limited ability to make coherent value judgments from inherently biased real world data sets (Lindebaum et al., 2020). This inherent bias in AI tools is further amplified due to incomplete and/or poor data quality, and by the programming errors (Boillet, 2018). To minimise such bias, a contextually embedded values-based understanding is necessary (Lindebaum et al., 2020).

The effects of automation bias, however, vary with the level of user expertise. Novice users tend to rely more on automation, more vulnerable to manipulation if technology-enabled tools are allowed to influence decision-making (Logg et al., 2019), and, tend to overreact and show greater decision bias than experts (Arnold et al., 2006; Sutton et al., 2023). With the automation of low-level audit tasks by AI tools, early career auditors will be able to perform tasks they might otherwise be unable to do (Sutton et al., 2023). They may perceive AI tools as an unchallengeable authority to which they can comfortably delete decision making responsibilities (Gunz and Thorne, 2020). In a study, novice users identified more control weaknesses when required to explore on their own, when compared to those relying on the system (Seow, 2011). In a study carried out in tax compliance context, Masselli et al. (2002) found novice users making detrimental decisions when faced with system prompts exhibiting automation bias while experienced users do not seem to overreact (Noga and Arnold, 2002). If these algorithms are not tailored to auditors' knowledge levels or lack appropriate context, auditors may blindly accept outcomes without adequate validation, leading to bias in decision making. This becomes especially problematic in a profession where individual judgment is central to maintaining auditors' expertise and professional status. It is, however, important to

It is however, important to note that the AI tools can reduce uncertainty for auditors, help them resolve disagreements with auditees as the data-driven evidence used to support audit conclusions is often regarded as objective ‘facts’ (Salijeni et al., 2019). Excessive reliance may result in auditors overlooking risks or factors not explicitly flagged by AI tools. Thus, over reliance on AI tools could not only weaken auditors' professional judgment but also reduce influence of auditees attempting to sway audit results (Dowling and Leech, 2014).

While identification and mitigation of biases is considered one way of addressing such AI-based biases, it often involves a trade-off between fairness and accuracy (Lee et al., 2019). Such cleaning of the dataset by eliminating naturally occurring real-world biases may no longer represent the context (Nishant et al., 2024). Another strategy is to add a human supervision layer. However, this may transform automated processes into semi-automated ones (Li, 2019) potentially losing the automation benefits. Further, collection, storage, and sharing of large datasets from auditees and public sources raises ethical concerns regarding data governance, privacy, data ownership, quality, and safety (Zandi et al., 2019).

Further, cognitive automation, facilitated by AI tools, risks diminishing human skills and expertise, particularly if individuals are held accountable for tasks they do not fully comprehend or cannot manage should the technology fail (Rinta-Kahila et al., 2023). This could reduce an individual's capacity to remain aware of ongoing activities, maintain competence and critically assess outcomes rendering the decision making biased (Rinta-Kahila et al., 2023).

Automation bias is well established and studied in the literature (Smaacchia et al 2024). Current information systems research examines bias as a technical challenge (Fu et al., 2021; Ahsen et al., 2019). While a technical approach is undoubtedly essential to address AI bias, it is important to recognize that artifacts based on AI technology are developed within highly complex contexts shaped by diverse social dynamics (Dignum, 2023). It is therefore necessary to consider not only the mathematical and computational constructs, but also the values and behaviours of those involved in the developing and deploying the application, the environmental context, organizational processes, and the interactions with end users (Akter et al., 2021; Schwartz et al., 2022). NIST has called for human centric approach with a critical role to domain experts in the design, development and deployment of AI tools (Schartz et al., 2022). In a recent study, Nishant et al (2024), moving beyond a techno-centric focus, have demonstrated how the exclusive use of formal rationality in AI can perpetuate biases and poor decision-making. Our study addresses the calls for sociotechnical (Asatiani et al., 2021) and human-centric approaches (Schwartz et al., 2022) to understand better the causes and conditions of AI bias (Kordzadeh and Ghasemaghaei, 2021) and the strategies organisations employ to mitigate its consequent effects. Given the paucity of empirical research on the effects of AI in auditing (Dwivedi et al., 2019; Samiolo et al., 2023), further exploration of human-AI interaction and its broader influence is crucial, as emphasized by numerous scholars (Sutton et al., 2023; Samiolo et al., 2023; Murray et al., 2021).

METHOD

We use theory of technology dominance (TTD) (Arnold and Sutton, 1998) and its extension (Sutton et al., 2023) as a guiding framework, and qualitative research methodology to analyse the automation bias AI use may cause in auditing. Our study explores the strategies accounting firms are employing to mitigate the automation bias caused by the continued use of AI tools in auditing. Extension of the theory of technology dominance, termed as TTD2, focuses on three interacting explanatory factors (Furnari et al 2021) – decision maker (novice auditor vs expert), decision (audit environment) context (experience with system, complexity, repetitiveness, pressure to make a decision) and AI technology/system design (restrictiveness, transparency, mandatory, collaborative vs adaptive) and explains how the configuration of these interacting parts lead to automation bias and complacency. TTD2 argues that the higher usage of AI-enabled systems, that are less transparent would lead to the development of poorer knowledge structure, attrition of users' expertise and risk of deskilling. Our study focuses on one effect - automation bias, theorised in the model.

A cross-sectional field study using qualitative research methodology is employed. Our approach enables an understanding of the informants' experiences and perceptions on the influence of automation bias engendered using AI enabled tools and make the context and challenges lucid to the reader (Dyer and Wilkins, 1991). As the use of AI-enabled tools in auditing is an intentionally driven change (Weick and Quinn, 1999) the views of decision-makers such as audit partners, technology specialists, and auditors and auditees reflect their attitudes, intentions, and perceptions regarding automation bias and automation complacency. Using a theoretical, non-random sampling approach, partners, and auditors (including novice auditors) and audit managers working in audit firms, and internal auditors were chosen as informants to provide empirical evidence. In addition, leaders from professional organisations were also interviewed as these bodies influence policies and skills related to the use of AI in auditing.

Semi-structured interviews with loosely structured interview guide was used for data collection. Interviews typically started with the respondent explaining his/her background and role in the firm, to understand the context and their perspective. This is followed by questions about the audit environment, AI tools used, and audit expertise. The study was approved by the authors' university ethics committee and data collection, analysis and reporting were carried out following ethics guidelines. Two pilot interviews were conducted to test interview guide (Yin, 2009), and a thematic analysis of the data was carried out independently by both researchers and reconciled. All the interviews were recorded with prior permission, transcribed and verbatim transcripts were sent to individual participants for validation and corrections if any, and then anonymized for analysis. So far, we have interviewed 14 respondents (4 senior partners, 4 early career auditors, 2 audit managers, 2 technology specialists and 2 senior managers in professional organisations. Interviews ranged from 30 to 90 minutes. Data from the transcripts was validated by analysing the transcripts and cross checking with the notes of observations made and analysed. One informant from the Big 4 auditing firm, one independent researcher and a colleague who did not participate in the study reviewed the analysis and a summary of findings. Some examples of the quotes are presented in the findings section. Table

ANALYSIS, DISCUSSION AND FINDINGS:

We found that the issue of automation bias is an ongoing concern for audit firms. Though AI technology is partially replacing auditors decision making capacity (Arnold et al., 2023), respondents believed that the AI tool they use helps them do their jobs better and "*does not remove from them the need to make decisions and judgments,*" (R1). Audit firms, our study noticed, are cognizant of the automation bias and its impact on decision making and audit quality and believed that these issues can be managed with careful deployment of AI tools designed to augment human capability (Samiolo et al., 2023).

Technology/AI system:

Audit firms are heavily investing in AI and developing proprietary AI tools jointly with technology partners, and using commonly available tools such as ChatGPT for their audit work. They are designed to work collaboratively with the user, their use is voluntary and requires human intervention and overview/supervision on the outputs, our study observed. While scholars had anticipated that the use of such tools would become mandatory (Boland et al., 2019; Dowling et al., 2018), our findings suggest otherwise.

The design of AI tools is intentionally narrow in scope, and their application is carefully controlled to minimise the automation bias and other deleterious effects of technology dominance. This controlled use is implemented primarily by not mandating the use of these tools for audit teams within the firm. In fact, mandatory use is not considered practical by the audit firms, we found. The evolving nature of the AI tool (Dwivedi et al., 2021) and the emphasis on the development of a tool that is compatible with the users and their expertise are the reasons why mandatory use is not the current policy.

A senior audit partner explained: "*No matter how hard we try to consider it upfront when we build, once it is launched, we find out a million more things that we need to accommodate before we could make it mandatory at scale. From our experience, its often a multi-year process from the time that we first launched a tool to when it is at a point where it is ready to be mandated. And some of those tools never get to that stage because there is so much diversity for that particular audit test that it is just wouldn't be practical to mandate*." (R2). Another respondent noted that it is "*not mandatory, but recommended; the goal is they put a huge investment in this tool so the goal is to make audit teams use the tool as much as possible, because the more you use it, the more you contribute to the model and give feedback on the functionality to the development team and it gets better and better*" (R15).

By making sure there is manual intervention and review of the output, firms are mitigating the effects of automation bias. As noted by a respondent, "*it is never going to be 100% accurate whether you use human or AI, but we need to embed a check in the process – both AI and manual*," (R2). Another audit manager reiterates the importance of manual review: "*when you send something out, you need to be responsible for the content that you're sending out, so you* *should always be reviewing the results* (produced by AI system). *To me, I think that's not optional. That's a mandatory, and that's what I said to my team as well. I wouldn't expect them to send me something without reviewing it from AI. I would not send anything without reviewing it because I'm not intending to use AI to just do the work for me, I'm using AI to do a better work. Yes I can use AI to save time, but I'm not sending the result directly to the client without me reviewing it.*" (R15).

By developing focused AI solutions for a particular audit task or a series of related audit tasks, standardizing it and deploying it across multiple audit engagements of similar nature, audit firms are minimising the potential impact of automation bias. Such strategy not only helps the firms to derive economies of scale (Huan and Vasarhelvyi, 2019), but also minimise the potential automation bias. Typically, firms develop use cases that are focused, relatively of low risk, repetitive in nature, scalable, tested and made available globally on a platform to provided assistance for achieving efficiencies.

Importantly, these tools are embedded in the workflow so that there is a manual intervention and final decision making. As observed by a respondent, the aim is to develop an "*end to end process for a certain section of the audit (for e.g., P&E additions, or operating expense test where there are a large volume of documents) where AI does first pass on testing and forwards to the auditor for review*." (R10). Such a strategy in the development of AI tool, "t*edious tasks are performed more efficiently by AI, and free up auditors to do more and make judgments in other areas,*" an informant observed (R13).

Explainability and visibility are considered important features of the AI tool that can help minimise automation bias. Though explainability, per say, is not a built-in feature of the AI tools currently deployed by the audit firms, our study observed that the processes are transparent and visible. This is because the tools are designed to automate mundane, tedious, low level and repetitive tasks that even early career auditors are not interested to carry out. As noted by a partner, these tools are developed for a specific area and are "*customizable to meet the needs of client business, considering the audit risks as seen by the firm; we frame the tool in terms of what the client would care about and what the audit partners are thinking in terms of audit risks that they want more visibility into to help clients and junior auditors who perform day to day tasks" (R8).*

Thus, visibility to help early career auditors to understand the process embedded in the AI tool is considered critical in the deployment to mitigate the risk of complacency and bias, and to retain and build expertise in the firm for those audit tasks (Rinta-Kahila et al., 2023).

The visibility and explainability required to be built into the tools are also influenced by the regulatory requirements. Auditors cannot rely on an AI tool when they cannot explain the model's inner workings, processes and outputs even if it is extremely efficient and produces consistently good quality outcomes. It is a requirement to comply with audit documentation standards (AICPA, 2020; CPAB, 2021; Boland et al., 2019). As ascertained by a respondent, if the processes in the tools *"are like huge black boxes and our audit standards do not require us to go deep into the processes, then we don't go for it*" (R7).

Audit environment (procedural & regulatory context):

Restricting the role of AI tools to tasks such as mapping, calculations and other repetitive tasks, allows audit firms to showcase their value to clients (R1, R6, R8, R12 & R14) while addressing concerns about automation bias and potential complacency. Respondents noted that the tasks auditors perform are primarily diagnostic and concentrated on groups of related activities (R1, R6 & R12). As a result, the AI tools in use do not contribute to increase in cognitive load, thereby minimising the risk of bias (Lyell and Coeira, 2017). Recognising that AI use and tools are in early stage, and that future would be different, one respondent opined that "t*here would be a lot of restrictions imposed on their design, deployment and use in future*" (R14) in terms of regulations and standards, not only to protect client's data but also to counter the potential effect of automation bias and complacency. Regulations on AI are still in nascent stage and standard setters are well behind technological developments (Seethamraju and Hecimovic, 2022). Because of these, big-4 firms, though have "*a strong technological competence (to develop more sophisticated AI tools), they don't integrate them into their audit practice*" (R4). They instead are using it (their technological competence) for consulting services and have already reported a significant revenue on AI-related services in the year 2023.

As stated by a partner, it is "*hard to get some of these techniques (employed in AI tool) to fit with the auditing standards where the thinking is that the computer is a record of the transaction rather than the computer (AI tool) is the transaction. Here it does not record what happened, it (AI tool) just makes it happen*" (R6). For the risk of non-compliance, audit firms are cautious and ensuring that the AI tool is designed to produce sensible outcome, and users are equipped with necessary skills to review and demonstrate to the client. Whilst, "*current thinking and algorithms are trained to replicate the thinking and decision-making of an expert auditor, we are not yet realising all the benefits AI can bring to audit, as these tools will be requiring audito*rs to explain to regulators *how AI arrives at conclusions*," a respondent observed (R4).

With regard to governance protocols in the organisation, respondents observed that there are no such strict protocols if the auditors are using their own platform which is secure. But if they are using other external AI tools, then there are very strict controls and protocols. A respondent states: "F*or Co-Pilot, it is actually a very strict protocol; before we can actually apply to have Co-Pilot installed, we have to remove all the client sensitive information from our laptop. Because for Co-Pilot you don't know like what can be read or who can access the data. Because sometimes people will do a client engagement where during the time they download the client data and then we do the review, the internal audit and other aspects, and then we submit the results back to the client. We have a very strict protocol that we cannot retain the information longer than necessary – whether it is for annuity client or it is a one-off engagement, the data will need to be erased and a very strict protocols are there to archive the information in a safe place; for certain reviews we must retain the evidence for the audit trail or for regulatory compliance.*" (R15).

Level of expertise – early career vs expert auditors:

While firms have developed AI tools tailored to specific audit areas, their implementation is carefully managed to ensure client acceptance, adherence to professional standards, and, most critically, comprehension by auditors of all experience levels to mitigate potential automation bias and deskilling effects. By designing AI tools that are intuitive and easy for auditors to understand, making the processes transparent, and aligning tool functionality with auditors' skill levels for everyday use (Arnold et al., 2023), firms are effectively addressing the risk of automation bias while preserving and enhancing expert knowledge. Furthermore, our findings indicate that auditors are able to understand and explain the inner workings of the AI tools currently deployed in audit engagements, due to their visibility as required under audit documentation standards (CPAB, 2021).

Potential bias and complacency among early career auditors is still a concern in many audit firms and are addressing it through training and developing an appropriate mindset. It is the mindset early career auditors must develop, and firms must encourage them to do that. Comparing that with early career of the graduate, a senior manager observes: "*When you were a graduate, you just do the best thing you could, and you send your work to your manager, and then your manager will review it and tell you what good looks like and then you keep refining it*." (R15). But, there is a concern that "t*hey think why bother do it by myself when I can have the AI tool do it for me. So I think there is a bit of the education that people need these AI tools especially as graduates but they cannot rely on the AI to do the work for them, without actually developing the skillset themself. Early career auditors must have a mindset that they cannot rely on AI result completely; they need to actually believe that they can do better than the AI and just use AI to help them, not to replace them*." (R15).

Audit firms, our study observed, are training their early career auditors and graduates on how to use AI responsibly to mitigate the negative effects of technology dominance. Further, they are encouraging early career auditors tor each out to seniors and experts rather than becoming complacent by relying on AI tools. As noted by a respondent, "*for certain things, when it all comes to the question of quality output, you actually need someone with experience to answer you, I think they should still reach out to a human* (R10). On the question of whether it is the organisation (audit firm) or the individual auditor that should be responsible for right use of AI, many respondents suggested both.

Conclusions:

Our study analysed the potential automation bias consequent to the use of AI tools in auditing and identified the strategies audit firms are using to mitigate its effects. By examining these factors collectively, our research attempted to uncover how the interplay between the environment, technology, and individual roles shapes auditing practices and decision-making outcomes. We found, audit firms are exercising caution by ensuring that both auditors and AI tools possess the necessary skills and expertise to produce meaningful outcomes, aligning their capabilities accordingly (Arnold et al., 2023). Our study extends the findings of Samiolo et al (2023) by highlighting a concern that automating low-value audit tasks may deprive early-career auditors of opportunities to make sense of and reflect on these tasks. Gaining this experience is crucial for the development of novice auditors to counter the effects such as bias, complacency and deskilling. Our findings align with the study by Rinta-Kahila et al. (2023) and suggest that greater reliance on AI in the future may lead to complacency (Malaescu and Sutton, 2015), introduce bias (Lyell and Coiera, 2017), and create an illusion of competence in decision-making (Sutton et al., 2023). Such developments have the potential to fundamentally reshape the audit profession by influencing its professional identity (Susskind and Susskind, 2022).

Though there are more sophisticated AI tools available to perform higher level audit tasks, audit firms are concerned about the permanent loss of skills and the bias in decision making that might entail. As noted by a partner, "*to give the manual jobs to AI, both the AI tool and the auditor do need experience on those manual processes; if we automate a small portion of audit work with limited data inputs, then AI tool wouldn't have sufficient experience to work efficiently and be professionally sceptical; and if we give them* (AI tools) *things that involve high judgment, then auditors would lose experience* (R14*).* Thus, there is a need for audit firms to balance efficiency with other detrimental effects such as bias and loss of skills. Over reliance on AI could lead to a long-term loss of critical auditing skills therefore a need to preserve auditors' expertise for high-judgment tasks such as assessing management assumptions and methodologies for impairment of assets, is limiting their role in auditing. Our study, as discussed above, identified potential vulnerabilities and opportunities for better integration of AI systems in ways that mitigate automation bias and thereby preserve professional competence, encourage accountability, and maintain the integrity of auditing processes in an increasingly AI-driven landscape. Ultimately, this study aspires to contribute actionable insights into managing the balance between human expertise and AI capabilities, ensuring that technology serves as a complement rather than a replacement to critical human judgment.

References:

Almufadda, G., and Almezeini, N.A. (2022). Artificial Intelligence Applications in the Auditing Profession: A Literature Review. Journal of Emerging Technologies in Accounting, 19(2), 29-42. DOI: 10.2308/JETA-2020-083.

Ahsen, M.E., Ayvaci, M.U.S. and Raghunathan, S. 2019. "When algorithmic predictions use human-generated data: a bias-aware classification algorithm for breast cancer diagnosis," *Information Systems Research* (30:1), pp. 97–116.

Akter S, McCarthy G, Sajib S, et al. (2021) Algorithmic bias in data-driven innovation in the age of AI. *International Journal of Information Management* (60): 102387. https://doi.org/10.1016/j.ijinfomgt.2021.102387

Australian Financial Review (2024) "The faster-growing firms have one thing in common: AI," 19 November 2024, the Australian Financial Review.

Arnold, V. & Sutton, S. G. (1998). The theory of technology dominance: Understanding the impact of intelligent decision aids on decision maker's judgments. Advances in accounting behavioral research, 1(3), 175-194.

Arnold, V., Clark, N., Collier, P., Leech, S. & Sutton, S. (2006). The differential use and effect of knowledge-based system explanations in novice and expert judgment decisions. MIS Quarterly, 30, 79–97. https://doi.org/10.2307/25148718.

Arnold, V., Collier, P., Leech, S., Rose, J., Sutton, S., 2023. Can knowledge-based systems be designed to counteract deskilling effects? International Journal of Accounting Information Systems, 50, 100638 https://doi.org/10.1016/j.accfin.2023.100638.

Asatiani, A., E. Penttinen, T. Rinta-Kahila, and A. Salovaara. (2020). Implementation of automation as distributed cognition in knowledge work organizations: Six recommendations for managers, 40th International Conference on Information Systems, ICIS.

Boillet, J. (2018). Why AI is both a risk and a way to manage risk. EY. Available at: https://www.ey.com/en_gl/assurance/why-ai-is-both-arisk-and-a-way-to-manage-risk

Boland, C.M., Daughterty, B.E. and Dickins, D. (2019). Evidence of the Relationship between PCAOB Inspection Outcomes and the Use of Structured Audit Technologies. Auditing:

Dignum, V. 2023. "Responsible Artificial Intelligence-from Principles to Practice: A keynote at TheWebConf 2022," in: *ACM SIGIR Forum* (pp. 1–6). New York, USA.

Dowling, C. & Leech, S. (2014). A big 4 firm's use of information technology to control the audit process: How an audit support system is changing auditor behavior. Contemporary Accounting Reseasrch, 31, 230–252.

Dowling, C., Knechel W.R. and Moroney, R. (2018). Public Oversight of Audit Firms: The Slippery Slope of Enforcing Regulation. ABACUS, 54(3), 353-380.

Dwivedi, Y.K., Hughes, L., Ismagilova, E., and others (2021) "Artificial Intelligence (AI): Multidisciplinary perspectives on emerging challenges, opportunities, and agenda for research, practice and policy," International Journal of Information Management, 57, 101994.https://doi.org/10.1016/j.ijinfomgt.2019.08.002.

Dyer, W.G. & Wilkins, A.L. (1991). Better stories, not better constructs, to generate better theory: a rejoinder to Eisenhardt. Academy of Management Review 16(3): 613-619.

Fu, R., Huang, Y. and Singh P.V. 2021. "Crowds, lending, machine, and bias," *Information Systems Research* (32:1), pp. 72–92.

Furnari, S., Crilly, D., Misangyi, V., Greckhamer, T., Fiss, P. & Aguilera, R. (2021). Capturing causal complexity: Heuristics for configurational theorizing. Academy of Management Review, 46(4), 778-799.

Goldman Sachs (2023) "AI investment forecast to approach $200 billion globally by 2025," 1 August, 2023. Retrieved from: www.goldmansachs.com/insights/articles/ai-investment-forecast-to-approach-200-billion-globally-by-2025.html, on 27 Jan 2025.

Kordzadeh, N. and Ghasemaghaei, M. 2022. "Algorithmic bias: review, synthesis, and future research directions," *European Journal of Information Systems* (*31*:3), pp. 388-409.

Koreff, J., Baudot, L. & Sutton, S.G. 2023. "Exploring the Impact of Technology Dominance on Audit Professionalism through Data Analytic-Driven Healthcare Audits," Journal of Information Systems (37: 3), pp. 59-80.

KPMG (2024) "AI in financial reporting and audit: Navigating the new era," KPMG International, May 2024, publication number: 139348-G.

Logg, J.M., Minson, J.A. and Moore, D.A. (2019). Algorithm appreciation: People prefer algorithmic to human judgment. Organizational Behaviour and Human Decision Processes, 151, 90-103.

Lindebaum, D., Vesa, M. and Den Hond, F. 2020. "Insights from "the machine stops" to better understand rational assumptions in algorithmic decision making and its implications for organizations," *Academy of Management Review* (45:1), pp. 247–263.

Lyell, D. & Coiera, E. 2017. “Automation bias and verification complexity: a systematic review,” *Journal of American Medical Informatics Association* (24:2), pp. 423-431. https://doi.org/10.1093/jamia/ocw105.

Malaescu, I. and Sutton, S. 2015. “The effects of decision aid structural restrictiveness on cognitive load, perceived usefulness, and reuse intentions,” *International Journal of Accounting Information Systems* (17), pp. 16–36.

Mehrabi, N., Morstatter, F., Saxena, N., Lerman, K. and Galstyan, A. 2021. “A Survey on Bias and Fairness in Machine Learning,” *ACM Computing Surveys* (54:6), pp. 1-35.

Mikalef, P., Conboy, K., Lundström, J. E. and Popovič, A. 2022. “Thinking responsibly about responsible AI and ‘the dark side’ of AI,” *European Journal of Information Systems* (31:3), pp. 257-268.

Murray, A., Rhymer, J. and Sirmon, D.G. 2021. “Humans and technology: forms of conjoined agency in organizations,” *Academy of Management Review*, (46:3), pp. 552-571.

Nishant, R., Schneckenberg, D. and Ravishankar, M.N. 2024. “The formal rationality of artificial intelligence-based algorithms and the problem of bias,” *Journal of Information Technology* (39:1), pp. 19-40.

PCAOB (Public Company Accounting Oversight Board) (2024). AS 1105 Audit Evidence, AS 1215 Audit Documentation, AS 2101 Audit Planning, Retrieved from: https://pcaobus.org/oversight/standards/auditing-standards

Rinta-Kahila, T., Penttinen, E., Salovaara, A., Soliman, W. & Ruissalo, J. 2023. “The Vicious Circles of Skill Erosion: A Case Study of Cognitive Automation,” *Journal of the Association for Information System*s (24:5), pp. 1378-1412. DOI: 10.17705/1jais.00829.

Samiolo, R., Spence, C. and Toh, D. 2023 “Auditor judgment in the fourth industrial revolution,” *Contemporary Accounting Research*, online. https://doi.org/10.1111/1911-3846.12901.

Schwartz, R., Vassilev, A., Greene, K., Perine, L., Burt, A., and Hall, P. 2022. T*owards a standard for identifying and managing bias in artificial intelligence.* US Department of Commerce, National Institute of Standards and Technology, 3.

Skitka, L.J., Mosier, K.L., Burdick, M. & Rosenblatt, B. 2000. “Automation bias and errors: are crews better than individuals? *International Journal of Aviation Psychology* (10:1), pp. 85-97.

Smacchia, M., Za, S., and Arenas, A.E. 2024. “Identifying AI Bias and Mitigation Challenges Through Socio-Technical Perspective,” *European Conference on Information Systems (ECIS 2024) Proceedings*, 12, https://aisel.aisnet.org/ecis2024/track03_ai/track03_ai/12.

Susskind, R. E. & Susskind, D. 2022. *The future of the profession: How technology will transform the work of human experts*, 2nd edition, Oxford University Press. USA.

Sutton, S.G., Arnold, V. and Holt, M. 2023. An extension of the theory of technology dominance: Capturing the underlying causal complexity. *International Journal of Accounting Information Systems* (50), 100626.

Tilbury, J. and Flowerday, S. 2024. “Automation Bias and Complacency in Security Operation Centers,” Computers (13:165), pp.1-22.

Vitali, S. and Giuliani, M. 2024. Emerging digital technologies and auditing firms: Opportunities and challenges,” International Journal of Accounting Information Systems (53), 100676. https://doi.org/10.1016/j.accinf.2024.100676

Weick K.E. & Quinn, R.E. 1999. “Organizational change and development,” *Annual Review of Psychology* (50), pp. 361–386.

Yin, R. 2009. Case Study Research: Design and Methods, Thousand Oaks, CA: Sage publications.

Paper #20

Title: Can AI Truly Learn? The Role of Consumers' Lay Beliefs in Algorithmic Aversion

Author(s): Rahul Banerjee and Aner Sela

Abstract:
This paper investigates how consumers' lay beliefs about learning influence their attitudes toward AI. It demonstrates that individuals with entity-based views (who see intelligence as fixed) are more likely to reject algorithmic decisions compared to those with incremental views. These insights help explain algorithm aversion and offer implications for designing consumer-facing AI systems.

Keywords: Artificial Intelligence, Algorithm Aversion, Consumer Behavior, Lay Beliefs, Human–Machine Interaction

Can AI truly learn? The role of consumer's lay beliefs in algorithmic aversion

ABSTRACT

This paper examines the influence of an individual's mindset on their willingness to adopt AI-generated recommendations, focusing on the mediating role of perceptions of AI's learning ability. Across two studies, we investigate how contextual and psychological factors shape user perceptions and behaviors toward AI systems. In Study 1, a field experiment with a sales team at a global technology consulting organization tested the relationship between mindset and willingness to use AI recommendations. The findings reveal that perceptions of AI's learning ability significantly mediate this relationship, highlighting the critical role of user beliefs in shaping AI adoption. However, no significant moderating effect was found for the decision maker's expertise. Study 2, conducted at a large public university in the southeastern United States, explored the role of AI anthropomorphism in shaping mindset and perceptions of AI learning ability. Contrary to expectations, anthropomorphic characteristics did not significantly influence mindset or perceptions of AI's intelligence. However, the study found that anthropomorphism, perceptions of AI's learning ability, and willingness to use AI were significantly correlated, suggesting a more nuanced role of anthropomorphic design elements in fostering AI adoption. These findings advance theoretical understanding by integrating individual mindset, AI anthropomorphism, and perceptions of learning ability into the broader discourse on AI acceptance. Practitioners can leverage these insights to design AI systems that emphasize learning capabilities and selectively incorporate anthropomorphic features to enhance user trust and adoption.

Keywords: AI adoption, mindset, AI learning ability, AI anthropomorphism, decision-making expertise, Human-AI interaction, organizational behavior

INTRODUCTION

In today's digital landscape, algorithms have become an integral part of everyday life, influencing decisions across various domains. From Google's search and maps to Netflix's movie recommendations and ChatGPT's responses to questions, AI recommendation engines are designed to guide users toward optimal choices. These systems leverage vast amounts of data to replicate human decision-making processes, offering insights and predictions that are often beyond the reach of human cognition. However, despite their computational power and efficiency, AI systems are not infallible. Errors in AI recommendations, often stemming from limitations in training data or model design, can erode user trust and lead to a phenomenon known as algorithmic aversion.

Algorithmic aversion occurs when users reject AI-generated recommendations, even when these recommendations are demonstrably superior to human judgment. This aversion has significant implications for both consumers and businesses. For consumers, rejecting AI recommendations can result in missed opportunities to benefit from advanced technologies, such as smart cars, automated drones, and robotic surgeries. For businesses, algorithmic aversion can hinder the adoption of AI-driven innovations, reducing the potential for efficiency gains and market growth. Understanding the psychological and contextual factors that drive algorithmic aversion is therefore critical for fostering AI adoption and maximizing its societal benefits.

One key factor influencing algorithmic aversion is the user's lay beliefs about AI's learning ability. Unlike humans, who learn through experience and adaptation, AI systems are perceived as being limited by their initial programming and training data. This perception can lead to skepticism about the reliability and adaptability of AI recommendations, particularly in complex or high-stakes scenarios. For instance, would consumers trust an AI to file their taxes accurately or rely on a self-driving car in a busy metropolitan area? These questions highlight the importance of addressing user beliefs about AI's capabilities to mitigate algorithmic aversion.

The role of mindset in shaping user perceptions of AI is particularly noteworthy. Drawing on the Implicit Theory of Mindset (Dweck, 1999), individuals can be categorized as having either a growth mindset or a fixed mindset. Those with a growth mindset believe that intelligence and abilities can be developed through effort and learning, while those with a fixed mindset view these traits as innate and unchangeable. This distinction has profound implications for how users perceive AI's learning ability. Individuals with a growth mindset may be more inclined to trust AI systems, viewing them as capable of improvement over time. Conversely, those with a fixed mindset may be more skeptical, perceiving AI as static and prone to failure.

The implications of algorithmic aversion extend beyond individual decision-making to broader societal and organizational contexts. For example, in professional settings, such as sales forecasting or customer relationship management, algorithmic aversion can undermine the adoption of AI tools designed to enhance productivity and decision-making accuracy. Similarly, in consumer markets, resistance to AI-driven products and services can slow the pace of technological innovation and market penetration. Addressing these challenges requires a nuanced understanding of the psychological and contextual factors that influence user trust and acceptance of AI.

This paper seeks to advance the understanding of algorithmic aversion by exploring the interplay between individual mindset, perceptions of AI's learning ability, and contextual factors such as AI anthropomorphism and decision-maker expertise. By examining these relationships, the research aims to provide actionable insights for both researchers and practitioners. For researchers, the findings contribute to the growing body of literature on human-AI interaction, offering new perspectives on the psychological underpinnings of algorithmic aversion. For practitioners, the insights can inform the design of AI systems that emphasize learning capabilities and foster user trust, ultimately driving greater adoption and acceptance of AI technologies.

THEORETICAL BACKGROUND

In recent decades, the development of intelligent products has significantly advanced, leveraging technologies such as microchips, software, sensors, and advanced algorithms. These products, deemed "intelligent," demonstrate capabilities such as collecting, processing, and producing information, and in some cases, even "thinking" for themselves. A key dimension of such intelligence is the ability to learn, which refers to a product's capacity to store information and adapt to its environment by collecting data over time (Rijsdijk et al., 2007). For example, a Nest thermostat learns user preferences over time to optimize temperature settings. This paper focuses on how individuals' mindsets and their perceptions of learning abilities influence interactions with intelligent algorithms, particularly in the context of algorithmic aversion.

Algorithmic aversion refers to the tendency of individuals to avoid using algorithms, even when they outperform human decision-making. This aversion is often magnified when algorithms make errors, as people are generally more forgiving of human mistakes than algorithmic ones (B. J. Dietvorst et al., 2015; Hidalgo, 2021). Research suggests that this aversion can be mitigated by ensuring technology readiness and reducing algorithmic errors (Castelo et al., 2019; Longoni et al., 2019). Additionally, individuals' perceptions of an algorithm's learning ability, its capacity to improve over time—play a critical role in overcoming aversion (Reich & Maglio, 2020). For instance, consumers are more likely to trust algorithms that demonstrate the ability to learn from mistakes, as this signals adaptability and improvement.

Lay theories describe individuals' beliefs about the extent to which intelligence can be taught and improved. One such belief system is the implicit theory of mindset, which categorizes individuals as having either a growth mindset (believing intelligence and abilities can be developed) or a fixed mindset (believing intelligence is innate and unchangeable) (Dweck, 1999). This theory has been applied in various contexts, including consumer behavior, where it has been shown to influence product preferences and trust recovery after product failures (Murphy & Dweck, 2016). For example, individuals with a growth mindset are more likely to embrace products that help them learn and improve, while those with a fixed mindset prefer products that reinforce their self-image.

In the context of intelligent algorithms, mindset theory suggests that individuals with a growth mindset are more likely to perceive algorithms as capable of learning and improving over time. Conversely, those with a fixed mindset may view algorithms as static and incapable of adaptation. We posit that this perception directly impacts their willingness to adopt algorithmic recommendations. Research has also shown that mindsets can change over time through appropriate interventions, further emphasizing the importance of understanding this construct in the context of AI adoption (Limeri et al., 2023).

Anthropomorphism, or the attribution of human-like characteristics to non-human entities, has been shown to influence trust and engagement with AI systems. People tend to perceive anthropomorphized AI as more intelligent, credible, and effective in decision-making tasks (Koda & Maes, 1996; Nass et al., 1995). For instance, anthropomorphic design elements in AI systems, such as human-like avatars or conversational interfaces, can enhance user trust and reduce algorithmic aversion (Waytz et al., 2014). However, excessive anthropomorphism can lead to discomfort, known as the "uncanny valley" effect, where users find the AI's human-like features unsettling (Salles et al., 2020).

In the context of algorithmic learning, anthropomorphism may amplify users' perceptions of an AI's learning ability, as human-like traits signal adaptability and intelligence (Moussawi & Koufaris, 2019; Sun et al., 2024; Wagner & Schramm-Klein, 2019). This aligns with prior research suggesting that people respond to anthropomorphized AI (Hasan, 2023) as they would to humans, attributing social and cognitive characteristics that drive trust and adoption (Reeves & Nass, 1996).

The level of expertise of decision-makers also influences their reliance on algorithmic recommendations. Experienced professionals, who often rely on their own judgment, may exhibit greater algorithmic aversion compared to novices (Logg et al., 2019). This aversion stems from a belief that algorithms lack the contextual understanding and adaptability required for complex decision-making (Mahmud et al., 2022; Schecter et al., 2023). However, research suggests that providing users with control over algorithmic processes can reduce aversion and increase trust (B. J. Dietvorst et al., 2018). Additionally, individuals with greater expertise may be more critical of algorithms' learning abilities, further influencing their willingness to adopt AI systems.

THE PRESENT INVESTIGATION

Based on the theoretical background and existing literature, this study aims to investigate the relationships between individual mindset, perceptions of AI's learning ability, willingness to use AI recommendations, and the moderating effects of decision-maker expertise and AI anthropomorphism. Drawing from the implicit theory of mindset (Dweck, 1999), individuals with a growth mindset are more likely to view AI systems as capable of improvement and adaptation. This positive outlook may translate into a greater willingness to engage with and trust AI recommendations. Conversely, those with a fixed mindset may perceive AI as static and limited, potentially leading to greater resistance in adopting AI-generated forecasts.

H1: An individual's mindset influences their willingness to use an AI-based forecasting platform, with the effect of those with a fixed mindset being more pronounced than those with a growth mindset.

Building on the work of (Reich et al., 2023), we propose that an individual's mindset influences their perception of AI's capacity to learn and improve over time. These perceptions, in turn, affect the individual's willingness to use AI recommendations. Specifically, those with a growth mindset are more likely to perceive AI as capable of learning, which positively influences their willingness to use AI-generated forecasts.

H2: Perceptions of AI’s learning ability mediates the relationship between an individual’s mindset and their willingness to use the AI forecasting platform.

Prior research suggests that experts may exhibit greater algorithmic aversion due to overconfidence in their own abilities and skepticism towards AI's contextual understanding (Logg et al., 2019). We hypothesize that this effect extends to perceptions of AI's learning abilities, with experts being more critical of AI's capacity to learn and adapt in complex decision-making scenarios.

H3: An individual's level of expertise moderates the relationship between perceptions of AI's learning abilities and their willingness to use an AI forecast platform, such that those with greater expertise are less willing to use AI recommendations.

Anthropomorphic elements in AI systems have been shown to enhance user trust and engagement (Waytz et al., 2014). It has also been shown that anthropomorphized technology improves perceived intelligence (Banks et al., 2008). It stands to reason that if there is a spill-over effect of lay theories of intelligence from people to "human like AI", this will create an effect on an individual's perception of AI's intelligence. We propose that these human-like features may amplify the effect of an individual's mindset on their perceptions of AI's learning ability. Specifically, for individuals with a growth mindset, anthropomorphic cues may reinforce beliefs about AI's capacity to learn and improve, while for those with a fixed mindset, these cues may have a less pronounced effect.

H4: The degree of AI anthropomorphism moderates the relationship between an individual's mindset and their perception of AI's learning ability, with a higher degree of anthropomorphism increasing AI's perceived learning ability.

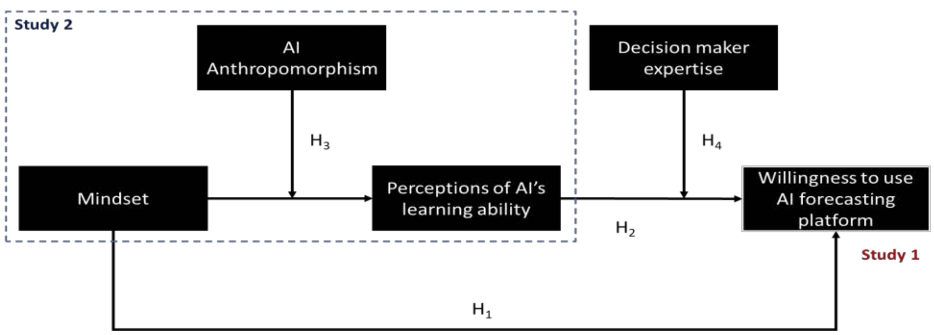


Figure 1: Conceptual Diagram

To test these hypotheses, we conducted two studies (See Figure 1). Study 1 focused on examining the relationships between mindset, perceptions of AI's learning ability, and willingness to use AI recommendations in a professional sales forecasting context. Study 2 extended this investigation by exploring the role of AI anthropomorphism in shaping user perceptions and behaviors in a consumer-oriented vacation planning scenario.

STUDY 1

A total of 668 participants working in the sales and account management functions at a large global technology consulting company were invited to participate in the study. These participants were selected because they regularly provide sales forecasts to management and are familiar with AI-enabled tools integrated into the company's internal portal, wiki, and customer relationship management (CRM) platforms. Out of the 668 invited participants, 117 responses were received (17.5% response rate), of which 60 responses were usable for the study (after eliminating incomplete responses and those with survey response bias). Participants were presented with a scenario-based survey where an AI algorithm provided a sales forecast for the current quarter based on data they had input into the CRM platform. The AI model was trained using data from the past two quarters, including the pipeline of deals, win/loss history, and accuracy of past forecasts. Participants were shown the AI's forecast alongside the actual total pipeline for the current quarter and were asked a) whether they agreed with the AI's forecast and whether they would be comfortable presenting the AI's forecast to senior management.

Participants then completed a survey measuring their mindset ($\alpha = 0.77$; adapted from (Dweck & Yeager, 2019)), perceptions of AI's learning ability ($\alpha = 0.86$; adapted from (B. Dietvorst et al., 2015)), willingness to use the AI platform ($\alpha = 0.78$; adapted from (Venkatesh & Davis, 2000; Wang et al., 2023)), and decision-maker expertise ($\alpha = 0.71$; adapted from (Clarkson et al., 2013; Logg et al., 2019)). Demographic data and employee tenure were also collected, and two attention checks were included to ensure coherent responses. The moderating effect of decision-maker expertise on the relationship between perceptions of AI's learning ability and willingness to use the AI platform was tested using the PROCESS SPSS macro (Hayes, 2022).

Results showed a significant relationship between an individual's mindset and their perceptions of AI's learning ability ($\beta=0.262$, $t=2.089$, $p=0.037$). Perceptions of AI's learning ability were significantly correlated with an individual's willingness to use the AI platform ($\beta=0.321$, $t=4.703$, $p<0.001$). The direct relationship between an individual's mindset and their willingness to use the AI platform was non-significant ($\beta=0.109$, $t=0.839$, $p=0.405$) and the moderating effect of decision-maker expertise on the relationship between perceptions of AI's learning ability and willingness to use the AI platform was not significant ($p=0.9484$).

STUDY 2

Building upon the insights gained from Study 1, which examined the relationship between mindset and willingness to adopt AI recommendations in a corporate setting, this second study delves into the rapidly evolving landscape of AI-powered vacation planning services. Recent studies have shown a significant relationship between an individual's mindset (Dweck & Yeager, 2019) and their propensity to adopt AI technologies. Specifically, individuals with a growth mindset, who believe that abilities can be developed, are more likely to anthropomorphize AI devices and exhibit more positive perceptions of AI technologies (Chen & Yi, 2024). Participants (N=489) were undergraduate students who volunteered to undertake this study in the consumer behavior lab at a large University in Southeast United States. Using a between subjects' design (level of AI anthropomorphism: high and low), study 2 investigates the role of AI anthropomorphism in shaping perceptions of AI's learning ability and ultimately, the willingness to use AI recommendations. Participants were asked to interact with a chatbot for two minutes to prepare a detailed family vacation plan with a couple of options in Costa Rica. In addition to mindset ($\alpha = 0.77$), perceptions of AI's learning ability ($\alpha = 0.86$) and willingness to use AI recommendation ($\alpha = 0.78$) were measured. Results revealed that a consumer's mindset is uncorrelated with their perceptions of AI's learning abilities or likelihood of following the recommendation. Consistent with that a mediation analysis (Hayes, 2022) testing the findings from the previous study (mindset → AI's learning ability → Follow recommendations) does not reveal a significant indirect effect. Further, a moderated mediation analysis with bootstrap (PROCESS Model 15; (Hayes, 2015)) with both anthropomorphism conditions as a moderator of the link between mindset and perceived learning ability does not reveal significant moderated mediation. The simple indirect effect of mindset on flowing the recommendation, through perceived learning ability, is not significant at either level of anthropomorphism. Interestingly, a simple mediation model with anthropomorphism condition as an independent variable, learning ability as the mediator, and following recommendation as a dependent variable, reveals a significant indirect effect ($\beta=0.309$, $t=2.653$, $p=0.008$). Although the direct effect of anthropomorphism on following the recommendation is not significant, it is possible that anthropomorphism increases perceived learning ability, and these perceptions increase trust in the AI bot and willingness to follow its recommendation.

GENERAL DISCUSSION

This research investigates the role of individual mindsets and perceptions of AI's learning ability in shaping algorithmic aversion and willingness to adopt AI recommendations. Across two studies, the findings highlight the nuanced interplay between psychological factors, such as mindset, and contextual factors, such as expertise and anthropomorphism, in influencing AI adoption.

Study 1 demonstrates that individuals with a growth mindset are more likely to perceive AI as capable of learning and improving over time, which positively impacts their willingness to use AI-enabled platforms. However, the direct relationship between mindset and willingness to use AI was not significant, suggesting that other factors, such as organizational norms or task-specific requirements, may play a more dominant role in professional settings. Additionally, decision-maker expertise did not significantly moderate the relationship between perceptions of AI's learning ability and willingness to use AI, indicating that expertise may not always translate into greater reliance on AI systems.

Study 2 extends these findings by exploring the role of AI anthropomorphism in shaping perceptions of AI's learning ability. While anthropomorphic design elements can enhance user perceptions of AI’s learning ability and therefore engagement and trust, excessive anthropomorphism may lead to discomfort, as suggested by the uncanny valley effect.

While research has shown that individuals with a growth mindset are more likely to perceive AI devices as human-like, particularly in interactions with intelligent personal assistants. However, as AI features become increasingly human-like, the effect of a growth mindset on anthropomorphism may diminish (Chen & Yi, 2024). This suggests that there might be a threshold effect in AI anthropomorphism where beyond a certain level, additional human-like features do not significantly impact perceptions. Secondly, cultural and generational factors specific to undergraduate students in the USA may have significantly influenced the results. A cross-cultural study (Folk et al., 2023) emphasized that cultural backgrounds and prior technological exposure significantly impacts how students perceive AI technology (Ma et al., 2024). The individualistic culture prevalent in the USA might lead to more varied or critical views of AI technologies, potentially overshadowing the expected effects of mindset and anthropomorphism. Furthermore, generational differences play a crucial role in shaping AI perceptions. Research has found that Generation Z students, which likely comprise the study's sample, are generally more optimistic about the potential benefits of AI compared to older generations (Chan & Lee, 2023). This generational optimism might have interacted with the study variables in unexpected ways, leading to results that deviated from the initial hypotheses.

Together, these studies contribute to a deeper understanding of the psychological and contextual factors influencing AI adoption. They also highlight the importance of designing AI systems that align with user mindsets and perceptions to mitigate algorithmic aversion and foster greater acceptance.

Theoretical contributions

By applying Dweck's implicit theory of mindset to the context of AI adoption, this study provides novel insights into how individual beliefs about intelligence and learning influence perceptions of AI's capabilities. This extends the application of mindset theory beyond human interactions to include interactions with intelligent systems. Our findings suggest that individuals with a growth mindset are more likely to perceive AI as capable of learning and improving, which positively influences their willingness to adopt AI recommendations. This contribution bridges the gap between cognitive psychology and technology acceptance models, offering a new perspective on the psychological underpinnings of AI adoption.

The study introduces and empirically validates the construct of perceived AI learning ability as a critical determinant of algorithmic aversion. This adds to the growing body of literature on algorithmic trust and acceptance by identifying a new psychological factor that influences user behavior. Our results demonstrate that perceptions of AI's learning ability mediate the relationship between mindset and willingness to use AI, highlighting the importance of user beliefs about AI's capacity for improvement in shaping adoption behaviors.

The research highlights the dual-edged nature of AI anthropomorphism. While human-like features can enhance trust and engagement, they can also lead to discomfort if overdone.

This finding contributes to the ongoing discourse on the design of AI systems and the psychological mechanisms underlying human-AI interactions. By examining the moderating effect of anthropomorphism on the relationship between mindset and perceptions of AI's learning ability, we provide a more nuanced understanding of how design elements influence user perceptions and behaviors.

Contrary to prior research suggesting that expertise reduces reliance on AI (Logg et al., 2019; Prahl & Van Swol, 2017), this study finds no significant moderating effect of expertise on perceptions of AI's learning ability. This challenges existing assumptions and calls for further investigation into the role of expertise in AI adoption. Our findings suggest that the relationship between expertise and AI acceptance may be more complex than previously thought, potentially influenced by contextual factors (Bigman & Gray, 2018) and the specific nature of the AI application.

By examining the interplay between mindset, perceptions of AI's learning ability, expertise, and anthropomorphism, this research provides a holistic framework for understanding the factors driving algorithmic aversion and acceptance. This integrated approach offers a more comprehensive view of AI adoption, acknowledging the complex interactions between individual psychological traits and contextual factors in shaping user behaviors.

These theoretical contributions advance our understanding of human-AI interactions and provide a foundation for future research in this rapidly evolving field. By elucidating the psychological mechanisms underlying AI adoption, this study offers valuable insights for researchers exploring the cognitive and social aspects of human-AI collaboration. Furthermore, these findings can inform the development of more nuanced models of technology acceptance that account for individual differences in mindset and perceptions of AI capabilities.

Practical implications

The findings of this research have important implications for practitioners, particularly in the design and deployment of AI systems and their use by consumers. We recommend that organizations consider incorporating features that emphasize AI's ability to learn and improve over time. For example, providing users with feedback on how the AI system has adapted based on their input can foster trust and reduce algorithmic aversion. This could involve implementing progress indicators or performance metrics that showcase the AI's learning curve and improvements over time. By making the learning process transparent, users are more likely to perceive the AI as capable of growth, aligning with their own growth mindset and increasing acceptance.

While anthropomorphic design elements can enhance user engagement, designers should avoid excessive human-like features that may trigger discomfort. Striking the right balance is crucial for fostering trust without alienating users. We suggest that practitioners conduct user testing to determine the optimal level of anthropomorphism for their specific application and target audience. This may involve experimenting with different avatars, voice interfaces, or conversational styles to find the sweet spot that enhances trust.

Study 2 identifies a relationship between AI anthropomorphism and perceptions of AI’s learning ability. The correlation implies that users who perceive AI as having strong learning abilities are more likely to trust its recommendations. We recommend marketers capitalize on this by emphasizing the adaptive and learning capabilities of their AI systems in customer communications. By showcasing how AI learns from user interactions to provide increasingly personalized recommendations, marketers can enhance the perceived value of their AI-driven services. To address algorithmic aversion, we recommend that organizations invest in training programs that educate users about AI's capabilities and limitations. This can help users develop a more accurate understanding of AI's learning ability and reduce resistance to its adoption. Training programs could include interactive demonstrations, case studies, and hands-on experiences that allow users to observe and interact with AI systems in controlled environments. By demystifying AI and highlighting its potential for improvement, organizations can cultivate a more receptive attitude among users.

Our findings suggest that the willingness to adopt AI may vary depending on the task and context. Practitioners should tailor AI systems to specific use cases and users need to maximize their effectiveness and acceptance. This may involve developing modular AI solutions that can be customized for different departments or roles within an organization. By aligning AI capabilities with specific job requirements and user expectations, organizations can increase the perceived relevance and usefulness of AI tools.

We also recommend that providing users with insights into how AI systems make decisions and learn from mistakes can enhance trust and reduce aversion. Transparency is particularly important in high-stakes contexts, such as healthcare and finance, where users may be more skeptical of AI recommendations. We suggest practitioners consider implementing explainable AI techniques that allow users to understand the reasoning behind AI-generated recommendations. This could include visual representations of decision trees, confidence scores, or natural language explanations of AI outputs.

We recommend that to cater to individual differences in mindset and perceptions of AI, practitioners consider developing adaptive interfaces that can adjust their level of complexity and autonomy based on user preferences and comfort levels. This personalized approach can help users gradually build trust in AI systems at their own pace, potentially shifting their mindset towards a more growth-oriented perspective over time. Implementing AI systems that align with user mindsets and perceptions requires collaboration between technical teams, user experience designers, and behavioral scientists. We recommend that organizations foster cross-functional teams that can integrate insights from psychology, design, and AI development to create more user-centric and psychologically informed AI solutions.

Limitations

This research, while providing valuable insights into the role of individual mindsets and perceptions of AI's learning ability in shaping algorithmic aversion, is not without its limitations. First, the generalizability of the findings may be constrained by the specific contexts in which the studies were conducted. Study 1 was conducted within a corporate sales environment, focusing on professionals familiar with AI tools, while Study 2 targeted undergraduate students in a controlled laboratory setting. These distinct participant pools may limit the applicability of the results to broader populations, particularly those with varying levels of exposure to AI technologies.

Second, reliance on self-reported measures introduces the potential for response biases, such as social desirability bias or survey fatigue. Although validated scales were used, participants' subjective interpretations of the questions may have influenced their responses, particularly in areas such as mindset and perceptions of AI's learning ability.

Third, the experimental design of Study 2, which manipulated anthropomorphic features of AI, may not fully capture the complexity of real-world interactions with AI systems. The artificial nature of the laboratory setting and the limited scope of the tasks assigned to participants may not reflect the nuanced and dynamic ways in which users engage with AI in everyday life.

Finally, the cross-sectional nature of the studies limits the ability to draw causal inferences about the relationships between mindset, perceptions of AI's learning ability, and willingness to use AI platforms. Longitudinal studies would be necessary to explore how these relationships evolve over time and in response to repeated interactions with AI systems.

Future Study Plan

We aim to offset the limitation of the sample used for Study 2 by diversifying participant samples to include individuals from different cultural, professional, and demographic backgrounds (using Prolific) in the next set of studies. This would enhance the generalizability of the findings and provide a more comprehensive understanding of how various factors influence algorithmic aversion across diverse populations.

Second, we propose to conduct these studies across cultures to study the impact of different cultures on the perceptions of AI’s learning ability instead of merely using a US based sample. We also propose employing a longitudinal research design to examine how perceptions of AI's learning ability and willingness to use AI platforms change over time to explore the impact of repeated interactions with AI systems, as well as the role of feedback and error correction in shaping user trust and adoption.

Third, we will delve deeper into the role of contextual factors, such as task complexity, decision stakes, and the specific domain of AI application (e.g., healthcare, education, or entertainment). Understanding how these factors interact with individual mindsets and perceptions of AI's learning ability would provide more actionable insights for designing AI systems that foster user trust and acceptance.

REFERENCES

Banks, M. R., Willoughby, L. M., & Banks, W. A. (2008). Animal-Assisted Therapy and Loneliness in Nursing Homes: Use of Robotic versus Living Dogs. *Journal of the American Medical Directors Association*, *9*(3), 173–177. https://doi.org/10.1016/j.jamda.2007.11.007

Bigman, Y. E., & Gray, K. (2018). People are averse to machines making moral decisions. *Cognition*, *181*, 21–34. https://doi.org/https://doi.org/10.1016/j.cognition.2018.08.003

Castelo, N., Bos, M. W., & Lehmann, D. R. (2019). Task-Dependent Algorithm Aversion. *Journal of Marketing Research*, *56*(5), 809–825. https://doi.org/10.1177/0022243719851788

Chan, C. K. Y., & Lee, K. K. W. (2023). The AI generation gap: Are Gen Z students more interested in adopting generative AI such as ChatGPT in teaching and learning than their Gen X and millennial generation teachers? *Smart Learning Environments*, *10*(1), 60. https://doi.org/10.1186/s40561-023-00269-3

Chen, Q. Q., & Yi, Y. (2024). Mindsets and mirrors: How growth mindsets shape anthropomorphism in AI-enabled technologies. *Psychology & Marketing*, *41*(12), 3072–3090. https://doi.org/10.1002/mar.22108

Clarkson, J. J., Janiszewski, C., & Cinelli, M. D. (2013). The Desire for Consumption Knowledge. *Journal of Consumer Research*, *39*(6), 1313–1329. https://doi.org/10.1086/668535

Dietvorst, B. J., Simmons, J. P., & Massey, C. (2015). Algorithm aversion: People erroneously avoid algorithms after seeing them err. *Journal of Experimental Psychology: General*, *144*(1), 114–126. https://doi.org/10.1037/xge0000033

Dietvorst, B. J., Simmons, J. P., & Massey, C. (2018). Overcoming Algorithm Aversion: People Will Use Imperfect Algorithms If They Can (Even Slightly) Modify Them. *Management Science*, *64*(3), 1155–1170. https://doi.org/10.1287/mnsc.2016.2643

Dietvorst, B., Simmons, J., & Massey, C. (2015). Supplemental Material for Algorithm Aversion: People Erroneously Avoid Algorithms After Seeing Them Err. *Journal of Experimental Psychology: General*. https://doi.org/10.1037/xge0000033.supp

Dweck, C. S. (1999). Self-theories: Their role in motivation, personality, and development. In *Self-theories: Their role in motivation, personality, and development.* Psychology Press. https://psycnet.apa.org/record/1999-02577-000

Dweck, C. S., & Yeager, D. S. (2019). Mindsets: A View From Two Eras. *Perspectives on Psychological Science*, *14*(3), 481–496. https://doi.org/10.1177/1745691618804166

Folk, D. P., Wu, C., & Heine, S. (2023). *Cultural Variation in Attitudes Towards Social Chatbots*. https://doi.org/10.31234/osf.io/wc895

Hasan, A. (2023). Why you are (probably) anthropomorphizing AI. *Philosophy Documentation Center*.

Hayes, A. F. (2015). An Index and Test of Linear Moderated Mediation. *Multivariate Behavioral Research*, *50*(1), 1–22. https://doi.org/10.1080/00273171.2014.962683

Hayes, A. F. (2022). *Introduction to Mediation, Moderation, and Conditional Process Analysis: A Regression-Based Approach* (Vol. 3). The Guilford Press.

Hidalgo, C. A. (2021, November 8). *Why We Forgive Humans More Readily Than Machines*. Scientific American. https://www.scientificamerican.com/article/why-we-forgive-humans-more-readily-than-machines/

Koda, T., & Maes, P. (1996). Agents with faces: the effect of personification. *Proceedings 5th IEEE International Workshop on Robot and Human Communication. RO-MAN'96 TSUKUBA*, 189–194. https://doi.org/10.1109/ROMAN.1996.568812

Limeri, L. B., Carter, N. T., Lyra, F., Martin, J., Mastronardo, H., Patel, J., & Dolan, E. L. (2023). Undergraduate Lay Theories of Abilities: Mindset, universality, and brilliance beliefs uniquely predict undergraduate educational outcomes. *CBE—Life Sciences Education*, *22*(4). https://doi.org/10.1187/cbe.22-12-0250

Logg, J. M., Minson, J. A., & Moore, D. A. (2019). Algorithm appreciation: People prefer algorithmic to human judgment. *Organizational Behavior and Human Decision Processes*, *151*, 90–103. https://doi.org/10.1016/j.obhdp.2018.12.005

Longoni, C., Bonezzi, A., & Morewedge, C. K. (2019). Resistance to Medical Artificial Intelligence. *Journal of Consumer Research*, *46*(4), 629–650. https://doi.org/10.1093/jcr/ucz013

Ma, D., Akram, H., & Chen, H. (2024). Artificial Intelligence in Higher Education: A Cross-Cultural Examination of Students' Behavioral Intentions and Attitudes. *The International Review of Research in Open and Distributed Learning*, *25*(3), 134–157. https://doi.org/10.19173/irrodl.v25i3.7703

Mahmud, H., Islam, A. K. M. N., Ahmed, S. I., & Smolander, K. (2022). What influences algorithmic decision-making? A systematic literature review on algorithm aversion. *Technological Forecasting and Social Change*, *175*, 121390. https://doi.org/10.1016/j.techfore.2021.121390

Moussawi, S., & Koufaris, M. (2019, January 8). Perceived Intelligence and Perceived Anthropomorphism of Personal Intelligent Agents: Scale Development and Validation. *Hawaii International Conference on System Sciences*. https://doi.org/10.24251/HICSS.2019.015

Murphy, M. C., & Dweck, C. S. (2016). Mindsets shape consumer behavior. *Journal of Consumer Psychology*, *26*(1), 127–136. https://doi.org/10.1016/j.jcps.2015.06.005

Nass, C., Moon, Y., Fogg, B. J., Reeves, B., & Dryer, C. (1995). Can computer personalities be human personalities? *Conference Companion on Human Factors in Computing Systems - CHI '95*, 228–229. https://doi.org/10.1145/223355.223538

Prahl, A., & Van Swol, L. (2017). Understanding algorithm aversion: When is advice from automation discounted? *Journal of Forecasting*, *36*(6), 691–702. https://doi.org/10.1002/for.2464

Reeves, B., & Nass, C. (1996). The Media Equation: How People Treat Computers, Television, and New Media Like Real People and Pla. *Bibliovault OAI Repository, the University of Chicago Press*.

Reich, T., Kaju, A., & Maglio, S. J. (2023). How to overcome algorithm aversion: Learning from mistakes. *Journal of Consumer Psychology*, *33*(2), 285–302. https://doi.org/10.1002/jcpy.1313

Reich, T., & Maglio, S. J. (2020). Featuring Mistakes: The Persuasive Impact of Purchase Mistakes in Online Reviews. *Journal of Marketing*, *84*(1), 52–65. https://doi.org/10.1177/0022242919882428

Rijsdijk, S., Hultink, E., & Diamantopoulos, A. (2007). Product Intelligence: Its Conceptualization, Measurement and Impact on Consumer Satisfaction. *Erasmus Research Institute of Management (ERIM), ERIM Is the Joint Research Institute of the Rotterdam School of Management, Erasmus University and the Erasmus School of Economics (ESE) at Erasmus Uni, Research Paper*, *35*. https://doi.org/10.1007/s11747-007-0040-6

Salles, A., Evers, K., & Farisco, M. (2020). Anthropomorphism in AI. *AJOB Neuroscience*, *11*(2), 88–95. https://doi.org/10.1080/21507740.2020.1740350

Schecter, A., Bogert, E., & Lauharatanahirun, N. (2023). Algorithmic appreciation or aversion? The moderating effects of uncertainty on algorithmic decision making. *Extended Abstracts of the 2023 CHI Conference on Human Factors in Computing Systems*, 1–8. https://doi.org/10.1145/3544549.3585908

Sun, Y., Chen, J., & Sundar, S. S. (2024). Chatbot ads with a human touch: A test of anthropomorphism, interactivity, and narrativity. *Journal of Business Research*, *172*, 114403. https://doi.org/10.1016/j.jbusres.2023.114403

Venkatesh, V., & Davis, F. D. (2000). A Theoretical Extension of the Technology Acceptance Model: Four Longitudinal Field Studies. *Management Science*, *46*(2), 186–204. https://doi.org/10.1287/mnsc.46.2.186.11926

Wagner, K., & Schramm-Klein, H. (2019). *Alexa, Are You Human? Investigating the Anthropomorphism of Digital Voice Assistants-A Qualitative Approach*. https://aisel.aisnet.org/icis2019/human_computer_interact/human_computer_interact/7

Wang, C., Ahmad, S. F., Bani Ahmad Ayassrah, A. Y. A., Awwad, E. M., Irshad, M., Ali, Y. A., Al-Razgan, M., Khan, Y., & Han, H. (2023). An empirical evaluation of technology acceptance model for Artificial Intelligence in E-commerce. *Heliyon*, *9*(8), e18349. https://doi.org/10.1016/j.heliyon.2023.e18349

Waytz, A., Heafner, J., & Epley, N. (2014). The mind in the machine: Anthropomorphism increases trust in an autonomous vehicle. *Journal of Experimental Social Psychology*, *52*, 113–117. https://doi.org/10.1016/j.jesp.2014.01.005

Paper #1

Title: Quality Management in Virtual Teams: A Comprehensive Research Framework

Author(s): Mahesh S. Raisinghani, Jared Snider, and Aykut H. Turan

Abstract:

This paper presents a research framework for understanding quality management in virtual teams. Through a literature review, it identifies communication, trust, leadership, and technology as critical factors influencing virtual project quality. The authors propose a model based on the Input-Process-Output approach, offering implications for both theory and practice. The framework emphasizes the need for advanced communication tools, trust-building strategies, adaptive leadership, and emerging technologies to enhance virtual team effectiveness.

Keywords: Virtual Teams, Trust, Technology, Leadership, Quality Management

Quality Management in Virtual Teams: A Comprehensive Research Framework

By

Mahesh S. Raisinghani, MAK College of Business and Entrepreneurship, Texas Woman's University, USA

mraisinghani@twu.edu

Jared Snider, University of Maryland Global Campus, USA

jsnider6@student.umgc.edu

and

Aykut H. Turan, Sakarya University, Esentepe Campus TURKEY

ahturan@sakarya.edu.tr

Abstract

This paper explores the intricacies of quality management in virtual teams, a necessity driven by the rise of remote collaboration facilitated by advanced communication technologies. The study identifies and examines critical factors influencing project quality, including communication, trust, leadership, and technology. Communication quality, characterized by clarity, accuracy, and timeliness, emerges as vital for maintaining project standards, though it is challenged by digital tool reliance. Trust, both swift and sustained, significantly impacts team dynamics, fostering collaboration and enhancing project outcomes. Leadership in virtual teams requires adaptability, with transformational and shared leadership styles proving effective. Technology serves as both an enabler and a barrier, necessitating strategic selection and utilization to support quality management. This literature review synthesizes findings to propose a comprehensive research framework grounded in the Input-Process-Output model, highlighting the interplay between these elements. The paper concludes with implications for theory and practice, emphasizing the need for advanced communication systems, trust-building strategies, leadership training, and the integration of emerging technologies to enhance virtual team performance and project quality.

Keywords: Virtual Teams, Trust, Technology and Quality Management, Implications

Introduction

The rise of virtual teams has reshaped the traditional work environment, compelling innovative approaches to project quality management. Advanced communication technologies have enabled remote collaboration, allowing teams to operate across geographic boundaries.

However, these developments introduce unique challenges in maintaining project quality standards. This literature review synthesizes findings from multiple sources to provide a detailed examination of project quality management in virtual teams, focusing on key themes such as communication, trust, leadership, and technology.

Communication Quality in Virtual Teams

Effective communication is foundational for managing project quality within virtual teams. Marlow et al. (2017) highlight that high-quality communication—characterized by clarity, accuracy, and timeliness—is essential for maintaining project cohesion and task accuracy. Virtual teams often struggle with communication quality due to their reliance on digital tools, which can lead to cognitive overload and asynchronous communication issues. To mitigate these challenges, closed-loop communication, where messages are confirmed and understood by all parties, is particularly critical in virtual settings (Marlow et al., 2017). This approach helps to ensure alignment with project goals and minimizes the risk of miscommunication.

Dulebohn and Hoch (2017) emphasize that effective communication systems are vital for virtual teams. The quality of communication directly influences the team's ability to manage project quality. Higher levels of virtuality demand more sophisticated communication and collaboration tools to maintain project standards. Effective communication is vital for overcoming challenges such as lower media richness and higher social distance, ensuring that all team members are on the same page regarding project objectives and deliverables (Dulebohn & Hoch, 2017).

Larson and DeChurch (2020) also discuss the role of communication in maintaining project quality within virtual teams. They suggest leveraging technology effectively to foster communication, collaboration, and trust among dispersed team members. Tools that provide richer media, such as video conferencing, can help bridge the gap created by the lack of face-to-face interactions, allowing for more expressive communication and reducing misunderstandings (Larson & DeChurch, 2020).

The quality of communication can greatly impact project quality management by ensuring that team members understand project goals, timelines, and expectations. Effective communication reduces the likelihood of errors, enhances coordination, and fosters a collaborative environment. By utilizing appropriate communication tools and practices, virtual teams can overcome the inherent challenges of remote work and maintain high standards of project quality.

Despite the emphasis on the importance of communication quality, several gaps in the literature highlight areas that need further exploration. Firstly, there is a notable lack of longitudinal studies. While current research underscores the significance of communication quality (Marlow et al., 2017; Dulebohn & Hoch, 2017; Larson & DeChurch, 2020), it often relies on cross-sectional data. Longitudinal research that tracks communication practices and their impacts on project quality over time is necessary to provide deeper insights into how communication evolves and influences project outcomes in virtual teams.

Moreover, the impact of emerging technologies on communication quality in virtual teams remains under-explored. Existing studies primarily discuss traditional communication tools like email, instant messaging, and video conferencing. However, the advent of advanced technologies, such as AI-based communication tools and virtual reality, presents new opportunities and challenges for virtual team communication. These emerging technologies could potentially transform communication dynamics, yet their effects on communication quality and project outcomes in virtual settings are not well understood. Exploring these technologies could provide valuable insights into enhancing communication strategies in virtual teams.

Trust in Virtual Teams

Trust is vital for managing project quality in virtual teams, as it influences various aspects of team dynamics, including communication, collaboration, and overall performance. Hacker et al. (2019) identify several types of trust relevant to virtual teams, such as swift trust, which develops quickly based on initial interactions, and sustained trust, which is built over time through consistent behavior. High levels of trust enhance collaboration, knowledge sharing, and team satisfaction, all of which are essential for maintaining project quality in virtual teams (Hacker et al., 2019). For instance, a longitudinal study by Marlow et al. (2017) found that teams with higher levels of trust had significantly better project outcomes, suggesting that trust is a critical factor in virtual team success.

Marlow et al. (2017) also highlight the importance of trust in virtual teams. Trust is more challenging to establish in virtual environments due to the lack of informal interpersonal interactions that typically occur in face-to-face settings. However, high-quality communication can help build and maintain trust among team members, which is central for effective collaboration and ensuring that project quality standards are met (Marlow et al., 2017).

Gilson et al. (2015) further emphasize the role of trust in project quality management in virtual teams. They suggest that trust significantly influences the success of virtual teams by enhancing communication, collaboration, and overall team performance. Effective communication behaviors, timely responses, open communication, and constructive feedback are essential for fostering trust. Higher levels of trust facilitate better knowledge transfer and exchange, which are necessary for maintaining high quality in project outputs (Gilson et al., 2015).

Trust directly affects project quality management by fostering a cooperative and reliable team environment. Trust enhances communication efficiency, promotes knowledge sharing, and improves team cohesion, all of which are vital for delivering high-quality project outcomes. Building and maintaining trust within virtual teams requires consistent, transparent, and proactive communication strategies.

Despite the consensus on the importance of trust in virtual teams, there are significant gaps in the literature that need further investigation. One key area that remains under-researched is the development of swift trust. While Hacker et al. (2019) identifies swift trust as a critical type of trust that forms quickly based on initial interactions, there is limited research on the specific mechanisms and processes that foster swift trust in newly formed virtual teams. Understanding these mechanisms is key for designing strategies that can effectively build trust from the outset in virtual team settings.

Additionally, there is a lack of detailed studies on how sustained trust evolves over long-term projects and its direct impact on project quality and team performance. Most existing research focuses on the initial stages of trust formation or on general trust dynamics without examining the long-term evolution of trust in virtual teams. Longitudinal studies that track the development and maintenance of trust over the lifecycle of a project could provide valuable insights into how trust influences project outcomes over time.

Leadership in Virtual Teams

Leadership is central to managing project quality within virtual teams. Hoch and Kozlowski (2012) emphasize the importance of both hierarchical and shared leadership in virtual settings. Hierarchical leadership may be less effective in virtual teams due to the lack of face-to-face interaction, which makes maintaining high-quality standards through direct oversight challenging. In contrast, shared leadership, characterized by collaborative decision-making and distributed responsibilities, fosters stronger team cohesion and a commitment to quality outcomes (Hoch & Kozlowski, 2012). Transformational leadership, which focuses on inspiration, motivation, and individualized consideration, has also been found to be particularly effective in virtual environments (Dulebohn & Hoch, 2017). This leadership style helps build trust, foster a positive team culture, and align team members with project goals, thus enhancing overall team performance and quality.

Larson and DeChurch (2020) explore different perspectives on leadership in virtual teams. They emphasize that leaders must adapt their strategies to the virtual environment, leveraging technology to support team processes and ensuring continuous feedback to maintain high-quality standards. Transformational leadership styles, which emphasize inspiration, motivation, and individualized consideration, are particularly effective in virtual environments. Transformational leaders can build trust, foster a positive team culture, and align team members with project goals, thus enhancing overall team performance and quality (Larson & DeChurch, 2020).

Dulebohn and Hoch (2017) also highlight the role of leadership in virtual teams. They suggest that leaders need specific skills to manage the lack of face-to-face interaction, including advanced communication skills, cultural awareness, and the ability to build trust and relationships remotely. Transformational leadership behaviors such as inspirational motivation and individualized consideration are particularly beneficial in fostering a high-quality virtual team environment, ensuring that project quality standards are upheld (Dulebohn & Hoch, 2017).

Leadership significantly influences project quality management in virtual teams by setting clear expectations, fostering collaboration, and motivating team members. Effective leaders use technology to facilitate communication, build trust, and ensure that team efforts are aligned with project goals, thereby enhancing overall project quality.

While the existing literature provides a comprehensive understanding of leadership's importance in virtual teams, several gaps remain that require further exploration. One significant gap is the limited comparative studies on the effectiveness of different leadership styles in various virtual team contexts. Although transformational leadership is frequently highlighted as effective (Larson & DeChurch, 2020; Dulebohn & Hoch, 2017), there is a scarcity of research comparing its effectiveness with other leadership styles, such as transactional or servant leadership, across different virtual team settings. Understanding these differences could provide a more nuanced perspective on which leadership styles are best suited for specific virtual environments.

Additionally, the literature lacks comprehensive frameworks or training programs focused on developing leadership skills specifically tailored for virtual environments. While the need for advanced communication skills, cultural awareness, and remote trust-building is recognized (Dulebohn & Hoch, 2017), there is little guidance on how to cultivate these skills effectively in leaders of virtual teams. Developing and evaluating targeted training programs could significantly enhance leadership effectiveness in virtual settings.

Technology and Quality Management

Technology is at the center of virtual teams. It’s impact on project quality management within virtual teams is twofold: it acts as both an enabler and a potential barrier. Larson and DeChurch (2020) emphasize that the effective utilization of technology is imperative for fostering communication, collaboration, and trust among dispersed team members. Technology affordances, such as real-time feedback and collaborative platforms, support continuous improvement and project quality management in virtual teams. However, technological challenges, such as delays in information exchange and reduced cohesiveness, must be addressed to ensure high-quality interactions and outputs (Larson & DeChurch, 2020).

Gilson et al. (2015) discuss the impact of various communication technologies on team dynamics and project quality management. While email and instant messaging are convenient for quick exchanges of information, they may lack the richness needed for complex discussions and decision-making. Video conferencing allows for more nuanced communication but may require more coordination and technological infrastructure. Advanced technologies, such as artificial intelligence (AI) and machine learning, can also play a role in project quality management by automating routine tasks, analyzing team performance data, and providing insights for improvement (Gilson et al., 2015).

Dulebohn and Hoch (2017) emphasize the importance of technology in project quality management. They note that the effectiveness of various communication technologies, such as email, instant messaging, and video conferencing, in supporting quality management practices has been mixed. Some studies indicate that certain technologies can enhance overall satisfaction and reduce social loafing, thereby improving team quality. However, other research highlights the limitations of traditional communication tools in ensuring high-quality interactions and outputs, suggesting a need for integrating newer technologies like 3D virtual environments and social media (Dulebohn & Hoch, 2017).

Technology plays a vital role in project quality management by enabling effective communication, coordination, and collaboration. The right technological tools can enhance team performance and project quality, while the wrong tools or poor implementation can hinder these processes. Therefore, selecting and leveraging appropriate technologies is crucial for maintaining high project quality standards in virtual teams.

While the literature underscores the importance of technology in facilitating project quality management in virtual teams, there are notable gaps that require further exploration. One key area is the adoption and integration of advanced technologies. Although the potential of AI and machine learning to enhance quality management practices is recognized (Gilson et al., 2015; Larson & DeChurch, 2020), there is a lack of empirical research investigating their actual impact on virtual team performance. Studies exploring how these technologies can be effectively integrated into existing workflows and their influence on project outcomes are necessary.

Moreover, research on technological adaptability and user training is limited. While Dulebohn and Hoch (2017) discuss the mixed effectiveness of various communication technologies, they do not address how virtual teams adapt to new technologies or the role of training programs in facilitating this adaptation. Understanding the processes through which teams adopt new technologies and the effectiveness of training programs in enhancing technology use and improving quality management practices is crucial. This could provide valuable insights into designing better support systems and training interventions for virtual teams.

Team Processes and Quality Outcomes

Effective team processes, including communication, coordination, and conflict management, are essential for maintaining high-quality standards in virtual teams. Gilson et al. (2015) highlight that synchronous communication tools can enhance team performance by reducing coordination delays. The quality of decision-making processes is influenced by the formalization of procedures and task interdependence, which can improve decision quality and team performance (Gilson et al., 2015).

Dulebohn and Hoch (2017) discuss several emergent states and processes that mediate the relationship between inputs and outcomes in virtual teams. Key processes include communication, collaboration, and technology usage. Effective communication is vital for overcoming the challenges of virtuality, such as lower media richness and higher social distance.

The development of shared mental models and trust among team members is necessary for maintaining quality and ensuring that team members are aligned with the project's goals and methods (Dulebohn & Hoch, 2017).

Hoch and Kozlowski (2012) emphasize the importance of shared leadership in enhancing team processes and quality outcomes. Shared leadership, characterized by collaborative decision-making and shared responsibility, can mitigate the disadvantages of virtual teams by fostering stronger interpersonal bonds and commitment to team goals. This collective approach to leadership ensures that quality management responsibilities are distributed, reducing the risk of oversight, and enhancing the overall quality of team outputs (Hoch & Kozlowski, 2012).

Efficient team processes are fundamental to maintaining project quality in virtual teams. Clear communication, effective coordination, and proactive conflict management help ensure that project tasks are completed accurately and on time. By fostering collaboration and aligning team efforts with project goals, virtual teams can achieve high-quality outcomes despite the challenges of remote work.

While the literature provides a thorough understanding of the importance of team processes in maintaining project quality, several gaps remain that need further exploration. One significant gap is the impact of team composition on processes. Existing studies often overlook how different team compositions, such as cultural diversity and varying skill levels, affect team processes and quality outcomes in virtual settings. Understanding these dynamics is crucial, as diverse teams may require different coordination and communication strategies to achieve optimal performance and quality outcomes.

Another critical gap is the lack of detailed research on conflict management strategies. While effective conflict management is recognized as vital for maintaining high-quality standards, there is limited understanding of which specific strategies are most effective in virtual teams. Identifying and analyzing the impact of various conflict management approaches can provide valuable insights into how virtual teams can better navigate conflicts to maintain project quality.

Research Framework and Model

Based on the synthesized literature reviews, a research framework for quality management in virtual teams can be developed. This framework integrates key elements such as communication, trust, leadership, and technology, highlighting their interrelationships and impact on team performance and quality outcomes.

Theoretical Foundation

The research framework is grounded in the Input-Process-Output (IPO) model, which is widely used in team research. According to the IPO model, team performance and outcomes are influenced by input factors (e.g., team composition, technology), process factors (e.g., communication, coordination), and output factors (e.g., performance, satisfaction). This model provides a structured approach to understanding the complexities of quality management in virtual teams.

Research Framework

The proposed framework for quality management in virtual teams consists of four primary components: inputs, processes, outputs, and moderators. These components work together to provide a comprehensive understanding of how virtual teams can achieve high-quality outcomes.

Inputs

Inputs represent the initial conditions and resources available to the virtual team. Key inputs include team composition, technology, and leadership style. Team composition refers to the diversity in skills, experience, and cultural backgrounds of team members. Technology encompasses communication tools, collaboration platforms, and advanced technologies like AI and machine learning. Leadership style includes transformational, transactional, and shared leadership approaches, which guide how teams are managed and motivated.

Processes

Processes are the mechanisms and activities that transform inputs into outputs. These include communication quality, trust development, coordination, and conflict management. Communication quality involves clarity, accuracy, timeliness, and the use of appropriate communication tools to ensure effective information exchange. Trust development focuses on mechanisms for building swift and sustained trust among team members. Coordination involves strategies for aligning team efforts and managing interdependencies to ensure cohesive teamwork. Conflict management includes techniques for resolving disagreements and maintaining a collaborative environment, which are essential for smooth team functioning.

Outputs

Outputs are the results of the team's efforts, which include project performance, team satisfaction, and knowledge sharing. Project performance is measured by the achievement of project goals, adherence to timelines, and the quality of deliverables. Team satisfaction gauges the contentment of team members with the team processes and outcomes. Knowledge sharing assesses the extent to which information and expertise are exchanged within the team, fostering a culture of continuous learning and improvement.

Moderators

Moderators are factors that influence the relationships between inputs, processes, and outputs. These include cultural diversity, skill levels, technology adaptability, and leadership adaptability. Cultural diversity examines the impact of diverse cultural backgrounds on team dynamics, which can affect communication and collaboration. Skill levels consider the variations in team members' expertise and experience, influencing their ability to contribute effectively to the project. Technology adaptability evaluates the team's ability to adopt and effectively use recent technologies, which is crucial for maintaining productivity and quality. Leadership adaptability assesses the leader’s ability to adjust their style to fit the virtual environment, ensuring that leadership remains effective despite the challenges of virtual team management.

By understanding and leveraging these components, organizations can enhance the quality of virtual team interactions and outputs, leading to improved performance and satisfaction among team members.

Research Propositions

Research Proposition 1:

High-quality communication positively impacts trust and team performance in virtual teams. Effective communication practices, such as closed-loop communication and optimal communication schedules, enhance team cohesion and task accuracy.

Research Proposition 2:

Trust moderates the relationship between communication quality and team performance. Higher levels of trust lead to better collaboration, knowledge sharing, and overall team satisfaction.

Research Proposition 3:

Transformational leadership positively influences team processes and quality outcomes. Leaders who inspire, motivate, and provide individualized consideration foster a positive team culture and align team members with organizational goals.

Research Proposition 4:

Effective utilization of technology enhances team coordination and quality outcomes. Technology affordances, such as real-time feedback and collaborative platforms, support continuous improvement and mitigate the challenges of virtuality.

Implications for Management

Organizations must prioritize the enhancement of communication systems to support clarity, accuracy, and timeliness. Investing in tools that provide rich media, such as video conferencing, can bridge communication gaps in virtual teams and reduce misunderstandings. Building both swift and sustained trust within virtual teams through consistent, transparent, and proactive communication strategies is crucial, as high levels of trust enhance collaboration, knowledge sharing, and overall team satisfaction. Leaders need to adapt their strategies to the virtual environment, leveraging technology to support team processes and providing continuous feedback. Transformational leadership, emphasizing inspiration, motivation, and individualized consideration, is particularly effective in virtual settings. Effective utilization of technology is critical for maintaining project quality. Organizations should integrate advanced technologies like AI and machine learning to enhance communication, automate routine tasks, and provide insights for continuous improvement. Developing targeted training programs that enhance virtual communication skills, cultural awareness, and trust-building capabilities is essential, as these programs can significantly improve the effectiveness of leaders and team members in virtual environments. Finally, efficient team processes, including clear communication, effective coordination, and proactive conflict management, are fundamental. Organizations should implement strategies that foster collaboration and align team efforts with project goals to achieve high-quality outcomes.

Implications for Research

There is a need for more longitudinal research that tracks communication practices and their impacts on project quality over time to provide deeper insights into how communication evolves and influences project outcomes in virtual teams. Further exploration is needed on the impact of advanced technologies such as AI-based communication tools and virtual reality on communication quality and project outcomes, with empirical research necessary to understand how these technologies can be integrated into existing workflows. Understanding the specific mechanisms and processes that foster swift trust in newly formed virtual teams requires more detailed research, which is essential for designing strategies that build trust from the outset. More detailed studies on how sustained trust evolves over long-term projects and its direct impact on project quality and team performance are needed, with longitudinal studies tracking trust development and maintenance over the project lifecycle providing valuable insights. There is also a scarcity of research comparing the effectiveness of different leadership styles, such as transformational, transactional, and servant leadership, across various virtual team settings.

Understanding these differences can offer a more nuanced perspective on effective leadership in virtual environments. Additionally, research on how virtual teams adapt to new technologies and the role of training programs in facilitating this adaptation is limited. Studies exploring these processes can provide valuable insights into designing better support systems and training interventions for virtual teams.

Implications for Theory

The evolving nature of virtual collaboration necessitates dynamic models that integrate trust, communication, and technology. Traditional theoretical frameworks should be adapted to reflect the complexities and fluidity of virtual team interactions. Theoretical frameworks should explore the interplay between different types of trust (swift and sustained) and the impact of technological advancements on team processes and outcomes. Understanding these relationships can provide a more comprehensive understanding of virtual team dynamics. The impact of advanced technologies such as AI, machine learning, and virtual reality on team dynamics and quality management should be incorporated into theoretical models, helping in predicting and explaining the influence of these technologies on virtual team performance. Theories should include longitudinal perspectives to understand how communication practices, trust development, and leadership effectiveness evolve over time in virtual teams, offering deeper insights into the long-term impacts of these factors on project quality.

Implications for Practice

Organizations should invest in advanced communication systems that support high-quality interactions, with tools that provide richer media, such as video conferencing and collaborative platforms, to mitigate the challenges of virtual communication. Practical strategies for building and maintaining both swift and sustained trust within virtual teams is crucial. This includes fostering transparent and proactive communication, providing timely feedback, and ensuring consistent behavior. Training programs focused on developing leadership skills tailored for virtual environments are essential. Leaders should be equipped with advanced communication skills, cultural awareness, and remote trust-building capabilities to effectively manage virtual teams. Effective utilization of technology is critical for maintaining project quality. Organizations should explore and integrate advanced technologies such as AI and machine learning to enhance communication, automate routine tasks, and provide insights for continuous improvement. Implementing clear communication protocols, effective coordination strategies, and proactive conflict management can help virtual teams maintain high-quality standards. Organizations should focus on fostering collaboration and aligning team efforts with project goals. Continuous training programs that enhance technological adaptability and user proficiency are necessary. Ensuring that team members are well-versed in new technologies and effective communication practices can significantly improve virtual team performance.

Conclusion

Effective quality management in virtual teams hinges on several key elements: communication, trust, leadership, and technology. High-quality communication, characterized by clarity, accuracy, and timeliness, is foundational as it impacts team cohesion, task accuracy, and overall project performance. Trust fosters a cooperative team environment, enhancing communication efficiency and knowledge sharing, and is built through consistent, transparent, and proactive strategies.

Leadership within virtual teams must adapt to the lack of face-to-face interaction, with transformational leadership proving particularly effective. Such leadership styles foster a positive team culture and align members with project goals, enhancing overall team performance and quality. Shared leadership, characterized by collaborative decision-making and distributed responsibilities, also strengthens team cohesion and commitment to quality outcomes. Technology, when appropriately selected and implemented, facilitates effective communication, coordination, and collaboration, thereby maintaining high project quality standards.

Despite extensive research, gaps remain, such as the need for longitudinal studies to track communication practices and their impacts over time. Further exploration is required on the effects of emerging technologies like AI-based tools on communication quality and project outcomes. Understanding the development of swift and sustained trust in virtual teams, comparing different leadership styles, and developing targeted training programs for virtual leaders are essential areas for future research. By addressing these gaps, organizations can enhance virtual team interactions and outputs, leading to improved performance and satisfaction.

References

Dulebohn, J. H., & Hoch, J. E. (2017). Virtual teams in organizations. *Human Resource Management Review, 27*(4), 569-574. http://dx.doi.org/10.1016/j.hrmr.2016.12.004

Gilson, L. L., Maynard, M. T., Jones Young, N. C., Vartiainen, M., & Hakonen, M. (2015). Virtual teams research: 10 years, 10 themes, and 10 opportunities. *Journal of Management, 41*(5), 1313-1337. https://doi.org/10.1177/0149206314559946

Hacker, J., Johnson, M., Saunders, C., & Thayer, A. L. (2019). Trust in virtual teams: A multidisciplinary review and integration. *Australasian Journal of Information Systems, 23*. https://doi.org/10.3127/ajis.v23i0.1757

Hoch, J. E., & Kozlowski, S. W. J. (2012). Leading virtual teams: Hierarchical leadership, structural supports, and shared team leadership. *Journal of Applied Psychology, 99*(3), 390-403. http://dx.doi.org/10.1037/a0030264

Larson, L., & DeChurch, L. A. (2020). Leading teams in the digital age: Four perspectives on technology and what they mean for leading teams. *The Leadership Quarterly, 31*(1), 101377. https://doi.org/10.1016/j.leaqua.2019.101377

Marlow, S. L., Lacerenza, C. N., & Salas, E. (2017). Communication in virtual teams: A conceptual framework and research agenda. *Human Resource Management Review, 27*(4), 575-589. https://doi.org/10.1016/j.hrmr.2016.12.005

Powell, A., Piccoli, G., & Ives, B. (2004). Virtual teams: A review of current literature and directions for future research. *The DATA BASE for Advances in Information Systems, 35*(1), 6-36. http://dx.doi.org/10.1145/968464.968467

Paper #8

Title: An Exploratory Study of the Impact of Influencer Marketing on the Online Purchase Intentions of Generation Z

Author(s): Deepti Aggarwal and Aayush Puri

Abstract:
This exploratory study examines how influencer marketing affects the online purchase intentions of Generation Z consumers. Using survey data and statistical analysis, the paper identifies trust, perceived authenticity, and content relevance as key factors influencing purchase behavior. The findings offer insights for marketers aiming to engage Gen Z audiences through digital platforms.

Keywords: Influencer Marketing, Generation Z, Online Purchase Intentions, Digital Marketing, Consumer Behavior

Evaluation of CRM Applications in E-commerce Marketplaces from the Perspective of Managers: A Case Study from Turkey

Abstract: This study aims to examine the CRM systems implemented in the marketplace model of a large e-commerce company in Turkey and to evaluate how these systems are perceived by managers and their effects.

Method: The main data of the study includes interviews with managers of an e-commerce company in Turkey. Within the scope of the research: Structured interviews were conducted on decision-making processes and challenges related to CRM applications. The findings were examined with thematic analysis method, especially focusing on the integration process of CRM, operational effects and critical success factors.

Findings: In the CRM integration process, compatibility of third-party tools, difficulties in data transfer and communication problems between stakeholders come to the fore. Coordination and cultural harmony between business units are of critical importance to overcome these difficulties.

With the integration of CRM, centralized management of data, replacement of manual processes with automation, and the possibility of personalization in customer relations have increased. This transformation has led to both operational and strategic improvements in business processes. CRM systems optimize the operational processes of businesses with their contributions in areas such as speed, automation, and data analytics. These systems provide businesses with a competitive advantage by providing efficiency in business processes.

While the integration of internal and external systems offers data management and cost advantages, third-party dependency and cultural differences stand out as disadvantages. In addition, top management support, effective data management, employee participation and communication play a critical role in the success of CRM integration. In addition, organizational culture and inter-unit collaboration are important elements that support the success of the process.

Results: It has been observed that CRM is not only a technology integration but also requires business processes and organizational culture to be made customer-focused and is much more than a technical process and creates organizational transformation in businesses. Factors such as top management support, cultural harmony, data management and communication are key to success. Literature and field study findings show that CRM not only provides operational benefits to businesses but also offers strategic advantages.

Keywords: CRM Application, E-commerce, Marketplace, Success CRM Implementation

1. Introduction

The efforts of businesses to ensure customer satisfaction, develop long-term customer relationships, and provide products and services that meet customer needs are critical to achieving competitive advantage today. In this context, Customer Relationship Management applications have become one of the most important strategic tools that businesses use to understand their customers, provide them with better service, and ultimately increase profitability.

With the impact of digital transformation in the business world, Customer Relationship Management (CRM) systems have become critically important for e-commerce platforms. CRM represents a strategic tool that companies use to increase customer satisfaction, create a loyal customer base, and maximize profitability.

This study aims to examine the CRM systems implemented in the marketplace model of a large e-commerce company in Turkey and to evaluate how these systems are perceived by managers and their effects.

2. Literature review

The concept of CRM was first born as a marketing strategy, but over time, with the development of information technologies, it has become a more comprehensive and strategic business model. In the in-depth literature analysis conducted by Al-Homery et al. (2023), it was stated that CRM is defined from three main perspectives: ***strategy, technology*** *and* ***process***. In this context, CRM is defined as not only a customer management tool, but also a strategy that covers all processes of customer-oriented business methods of enterprises.

Essentially, CRM is a strategy that businesses use to increase customer satisfaction. This strategy involves understanding customer needs, developing products and services that meet these needs, and offering them to the market. In addition, this process aims to maintain communication with the customer not only during the sales phase but also after the sale and to develop long-term relationships. Customer needs change constantly due to competitive markets and according to the field of trade. For this reason, companies determine their Customer Relationship Management strategies to maintain continuous communication with the customer, understand their needs, and provide better service.

CRM is also a business and marketing strategy that integrates process technology and all commercial activities around customers. Thus, companies can provide better service to their customers. When implementing CRM strategies, companies must meet the needs of their customers very quickly, effectively and efficiently. Therefore, having an application becomes a necessity for companies developing CRM strategies. However, CRM is not just an application. It is a business strategy that gives great importance to customers (Feinberg et al. 2002; Karagöl 2007).

CRM is a unit that focuses on the best management of customer relationships in a business. This unit includes analyzing customer data, monitoring customer interactions, and using the resulting data to provide better service. In addition, as Boulding et al. (2005) put it, CRM is not only a customer-centric orientation, but also an integration of the use of all relationships and systems to collect and analyze data across the firm, connecting the firm and customer value along the value chain and improving their ability to integrate them.

The main purpose of CRM strategies is to ensure customer satisfaction. Because satisfied customers tend to buy more, remain more loyal to the brand, and as a result, more profit is achieved. In this context, customer satisfaction is considered a central element of CRM strategies. It has also been stated that "CRM focuses on the relationship between an organization and its customers" (Stone and Laughlin 2016; Al-Homery et al. 2022) and is defined as "the process of carefully managing detailed information about individual customers and all customer 'touch points' to maximize loyalty" (Kotler and Keller 2011; Kampani and Jhamb 2020). Therefore, CRM is of great importance in the relationships that businesses maintain with their customers.

2.1. Critical Success Factors for Successful CRM Integration

A successful CRM implementation should increase knowledge management capabilities, data sharing capabilities, and willingness to share data, etc. Similarly, an unsuccessful implementation can have the opposite effect by making staff less willing to cooperate or use new technology (King and Burgess 2008; Mishra and Mishra 2009). Therefore, successful implementation of the CRM system is very important. Since 70% of CRM projects fail, it would be right to evaluate the success criteria at the project analysis stage. In this section, the critical success factors in CRM implementation will be shared in chronological order along with the important findings identified in the literature analysis.

According to Fotouhiyehpour (2006); in order to successfully implement CRM applications, the preparedness of the company should be carefully evaluated:

- Organizational Structure: The extent to which the company's organizational structure is suitable for CRM applications should be evaluated. For example, a customer-focused organizational structure facilitates the adoption of CRM.
- Employee Preparation: Necessary training and support programs should be organized to ensure that employees adopt and implement CRM practices.
- Investment and Cost: Since the implementation of CRM systems is a significant cost element, the return on these investments should be well calculated. The financial and commercial benefits of the company should be taken into consideration.

Additionally, there are some basic steps to be taken before moving on to CRM applications:

- Situation Analysis: A detailed analysis of the company's current CRM capacity and infrastructure should be conducted. This analysis will reveal which areas need development.
- Goal Setting: The strategic goals expected from CRM applications should be clearly defined.
- Pilot Applications: Before implementing CRM systems, the system should be tested with small-scale pilot applications and necessary improvements should be made.
- Cultural Adaptation: In order to implement CRM, the necessary changes may need to be made in the cultural structure of the company. This is especially important in terms of creating a customer-focused culture.

In order to achieve success in CRM strategies, companies need to take into account the developments in information technologies. Because customers and potential customers can easily access the data they need over the internet. The internet allows users (and customers) to instantly access various data due to the developments in information technologies. Therefore, business techniques change. A company in any part of the world can reach many potential and real customers located all over the world. This allows customers to choose from many companies to work with. With this concept, companies should focus on their relationships with customers over the internet. In today's competitive environment, finding and retaining customers has become more critical than ever. On the other hand, retaining customers is less costly than finding new ones. This shows that the internet and technologies have great power in achieving success in CRM strategies. (Kotorov 2003; Karagöl 2007)

Shum et al. (2008) emphasize in their studies that organizational competencies play an important role in the successful implementation of CRM systems. In particular, information technology management, customer data analysis and internal communication capabilities increase the effectiveness of CRM and positively affect sales performance. It is concluded that CRM is not only a technology but also an organizational change tool and that the entire organization must be involved in this process for this change to be successful.

Sauer's model classifies the list of CRM critical success factors as follows:

- Context: knowledge management capabilities, willingness to share data, willingness to change processes, technological readiness.
- Supports: senior management support.
- Project organization: Communication of CRM strategy, culture change capability and systems integration capability.

These three serve to connect the CRM critical success factors to the existing body of knowledge on the success/failure of information systems and to provide a higher level of abstraction to the list of success factors. They also suggest a set of higher-level relationships among the success factors. (Sauer et al. 1997; Mishra and Mishra 2009)

In his study, Almotairi (2009) conducted a literature analysis on successful CRM implementation and proposed the suggested framework according to CRM integration processes as follows;

- Phase 1: Integration preparation
    - Top management commitment
    - Clear determination of CRM strategy and vision

- Phase 2: Integration process
    - Data quality
    - Company culture change
    - Process change/structure redesign
    - Information technology management and integration competence
    - Talented, educated and motivated employees
    - Increased customer engagement/interaction
    - Alignment of all departments and running towards a common goal for CRM
- Phase 3: Post-application
    - Monitoring, controlling, measuring and feedback

Piskar and Faganel (2009) summarized the criteria for success as follows;

- Strategic Decision and Planning
- Training and User Acceptance
- Data Migration and Integration
- Harmonization of business processes with the CRM system
- Continuous Monitoring and Improvement
- Use of Analytical CRM

According to them, CRM implementation is not only a technology integration but also a holistic and complex process that requires making business processes and organizational culture customer-focused.

Ali et al. (2015) stated that the key factors that directly affect the success of e-CRM applications are the operational and strategic benefits of CRM applications, top management support, preparation of technological infrastructure and information management.

In addition, according to Widiantono and Sejati (2022), one of the most important factors regarding CRM requirements is understanding Information Management and integrating it correctly with CRM. The role of Information Management (KM) is critical in successfully fulfilling CRM requirements. KM acts as an effective tool in the processes of collecting, storing and transforming customer information into meaningful information. Correct integration of CRM systems with KM provides the opportunity to deeply understand customer relationships and use these relationships as a strategic advantage. This integration not only manages customer data, but also allows companies to personalize the products and services they offer to customers thanks to the information obtained by analyzing this data. Thus, customer satisfaction and loyalty are increased, and competitive advantage is strengthened. Therefore, the effectiveness of CRM processes is directly related to the correct understanding and implementation of Information Management.

Mollaee et al. (2023) interviewed 35 tourism companies about CRM processes and showed that successful CRM implementation in the tourism industry requires management support, organizational culture and commitment, and appropriate organizational literacy. Information Technology (IT) infrastructure and budget constraints are obstacles to the delivery project. Integrating organizational processes, training managers and staff, incentivizing and punishing employees, ensuring strategic alignment, providing technical infrastructure, ensuring adequate customer recognition, and developing appropriate budgets are stated as normative actions (or strategies) for successful implementation of CRM systems.

Table 1

Representation of Criteria for Successful CRM Implementation According to CRM Components

Success criteria	**Person**	**Technology**	**Period**
Top management support	x		
CRM Strategies	x		
Business Processes			x
Corporate culture	x		x
Technology infrastructure		x	

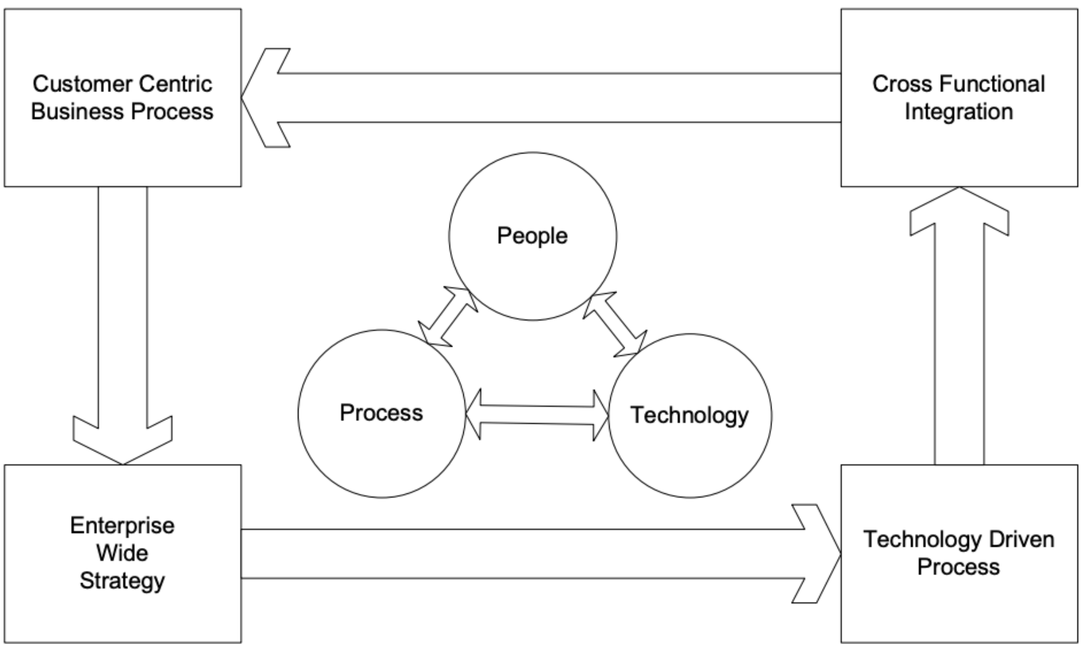
Database management	x	x

Source: Thai et al. (2024)

In the most recent study, Thai et al. (2024) presented the relationship between people, technology and process, which are the main CRM elements among the successful CRM application factors, as in Table 1.

Figure 1

CRM Integration Model



Source: Chen and Popovich (2003), cited in Fotouhiyehpour (2006)

All studies have proven that, as Chen and Popovich convey in the integration model in Figure 1, focusing on only one of the process, human and technology dimensions for successful CRM implementation is insufficient, and that all dimensions must work collectively and harmoniously towards a common goal in order to achieve success. In addition, while drawing attention to the importance of top management support, technological infrastructure, data and information management/hierarchy; a correct CRM strategy must be established and the entire company must be ready for this process and run towards a common goal, including changes in corporate culture and business practices.

2.2. Marketplace Business Model and Marketplace in E-Commerce

E-commerce encompasses a broad spectrum of business activities that allow businesses and individuals to buy and sell products and services online. This model of commerce refers to all commercial transactions conducted over computer-mediated business networks that result in the transfer of ownership or the right to use a service. Gupta (2014) has explained the basic types of e-commerce as follows;

- **B2B (Business to Business)** : A type of trade that takes place between businesses. Goods or services are sold between businesses such as suppliers, manufacturers and wholesalers. This type constitutes the largest share of e-commerce.
- **B2C (Business to Consumer)** : This is a model where businesses offer products and services to end consumers. Online retail stores are the best examples of this type. Consumers review product information online and make purchases through digital platforms**.**
- **C2C (Consumer to Consumer)** : This is a model where consumers trade among themselves. This type is widely used through second-hand product sales and online auction platforms. For example, platforms where interpersonal shopping is common are examples of the C2C model.
- **B2G (Business to Government)** : This is a model where businesses provide goods and services to public institutions. Public tenders and government digital service purchases fall into this category. This type allows public institutions to manage their procurement processes through digital platforms.
- **M-Commerce (Mobile Commerce):** Refers to electronic commerce transactions performed via mobile devices (smartphones, tablets, etc.). A sub-branch of e-commerce, m-commerce enables users to purchase products and services, make payments, and perform financial transactions via their mobile devices.

The marketplace business model, as an important element of the e-commerce ecosystem, offers digital platforms where multiple sellers and buyers meet. These platforms bring sellers and consumers together by offering a wide range of products and services and facilitate trade by reducing transaction costs. Marketplaces allow buyers to compare products and prices from different sellers, thus increasing transparency and competition in the market. At the same time, from the sellers' perspective, marketplaces offer the opportunity to reach a wider customer base and contribute to the facilitation of trade with support services such as logistics and payment systems.

The importance of marketplaces in e-commerce is increasing as they both reduce the marketing costs of businesses and speed up sales processes by improving customer experience. Marketplaces establish trust between buyers and sellers and ensure that transaction processes are completed quickly and reliably. In addition, they allow sellers to optimize their operational processes thanks to the integration of processes such as logistics and supply chain management. Kawa and Wałęsiak (2019) have revealed various advantages of marketplaces for both sellers and buyers in their studies. Especially for sellers, marketplaces provide access to large customer bases, while reducing costs and making sales processes more efficient. Buyers, on the other hand, have the opportunity to compare products and services from different sellers, find the best prices and choose from more options through marketplaces. In addition, marketplaces make transaction processes safer by providing various security and payment facilities in order to increase trust between buyers and sellers.

Being successful in digital markets is not limited to managing customer relationships alone, but also depends on businesses developing their ability to provide strategic services. While the marketplace business model brings together a large number of sellers and customers, CRM solutions play a key role in optimizing this complex structure and directing it with the right strategies. Lunn (2002) stated in his study that among the factors for achieving success in digital markets, providing specialized services, targeting the right buyers and sellers, and focusing on supplier participation, each of these factors increases the competitiveness of the business in the digital market, supported by the opportunities offered by CRM solutions.

2.3. CRM Usage in Marketplace Companies

The marketplace business model represents a multifaceted structure where various sellers and buyers come together on a platform. In this model, companies offer their products and services to a wide range of customers, while buyers have the opportunity to procure products from different suppliers. For marketplace companies, effectively managing customer relationships and optimizing this complex structure is critical to the efficiency of business processes. At this point, CRM solutions are an important tool that supports companies' processes of managing, analyzing and making strategic decisions about customer data.

The use of digital communication technologies in marketplace companies is indispensable for continuous and effective communication with customers. Høgevold et al. (2024) emphasize that CRM systems and social media tools play a key role in collecting customer and market information, making strategic decisions and improving sales performance. The integration of these technologies allows marketplace companies to respond quickly to customer demands and adapt more quickly to dynamic changes in the market. This contributes to increased customer satisfaction and maintaining competitive advantage in the market.

According to research by Høgevold et al. (2024), one of the important advantages that CRM solutions offer to marketplace companies is that they facilitate the achievement of sales targets by deeply analyzing customer data. CRM systems allow sales teams to develop more efficient strategies and analyze market trends using customer information. This process helps marketplace companies exceed their sales targets and increase customer satisfaction. Thus, companies make their operational processes more effective with digital marketing strategies while maintaining their competitiveness.

We also see that CRM solutions do not only provide economic gains, but are also effective in increasing employees' job satisfaction and emotional satisfaction. Høgevold et al. (2024) state that the use of CRM systems increases the economic and emotional satisfaction of sales teams, which contributes to a healthier management of customer relationships. This satisfaction plays an important role in companies' efforts to create long-term customer loyalty.

As stated in the study of Yong (2024), traditional B2B businesses have gained competitive advantage in the online environment by switching to digital marketing strategies. The adoption of digital channels such as website optimization, content marketing, and CRM integration allows them to provide more targeted services by increasing customer satisfaction. This use of digital tools is an important factor in the sustainable growth of marketplace companies.

Purwoko and Belgiawan (2024) proposed solutions to the deficiencies in marketing and CRM processes of Indonesia-based PT Oranye. These solutions include strengthening digital marketing strategies, standardizing CRM processes, and emphasizing technological innovations. It is predicted that by improving CRM processes, PT Oranye's position in the market will be strengthened and its business volume will increase.

Cardoso and Pacheco (2024) examined how B2B businesses continued their digital sales processes with the integration of social media and CRM during the COVID-19 period. Social media, especially through sales activities conducted through platforms such as LinkedIn, helped strengthen customer relationships and increase sales performance. The integration of CRM systems with social media allowed for more effective management of customer data and more accurate strategic decisions. These studies show how digital tools and CRM solutions can be used effectively in B2B sales even during times of crisis.

3. Method

In the previous section, CRM integration critical success factors, marketplace business model and CRM usage in marketplace companies literature analysis were shared. In this section, the purpose of the interview research conducted with the managers of the units that are stakeholders of the integration process after the marketplace CRM integration in one of the e-commerce giants in Turkey, the data collection-measurement process and findings will be shared.

3.1. Purpose of the Study

The purpose of this study is to measure the findings supported by the literature in the previous sections and transferred and identified for the e-commerce company marketplace CRM integration process.

The research was conducted to analyze the following issues from project management, information technology and commercial team/business unit perspectives;

- The most difficult points in the CRM integration process are,
- Advantages and disadvantages of the model where in-house and external software integration is used together,
- As a result of the integration, differences compared to the previous process,
- Contributions of CRM integration to the operational process,

- Critical success factors of CRM integration.

3.2. Data Collection and Analysis

In the study, the results of the e-commerce company marketplace CRM integration process were measured. An online survey was used to measure this and collect data.

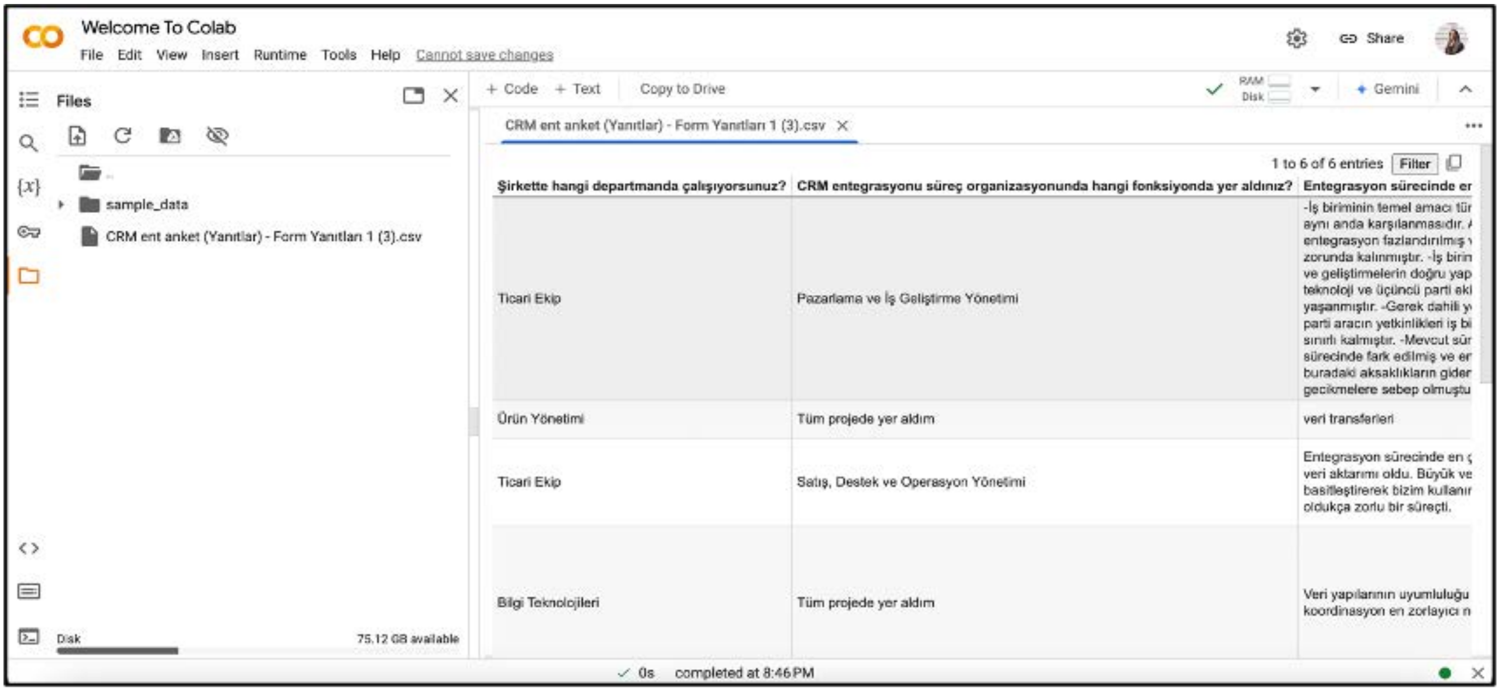
The survey is shared in Appendix-1 and there are 7 questions in total in the survey. While the first two questions are demographic, the other questions were added to measure important issues and success criteria related to the process. The data was collected from the managers of the marketplace product management, information technologies and commercial teams of the company, which is one of the e-commerce giants in Turkey where the CRM integration was carried out.

During the integration process, the Product Management unit monitored the entire process as a project manager, while the Information Technologies unit advanced its responsibilities of integrating the third-party company's vehicle with internal software development. The Commercial Team will use the CRM structure that emerges at the end of the integration process and is the unit that performs the entire CRM process.

Google Forums was used as an online survey tool. First, the survey results were exported in csv file format. Then, the survey results were uploaded to Google Colab, a cloud-based coding environment, as shown in Figure 2. Colab is a platform provided by Google that is used to conduct research projects, train machine learning models, and run Python code.

Figure 2

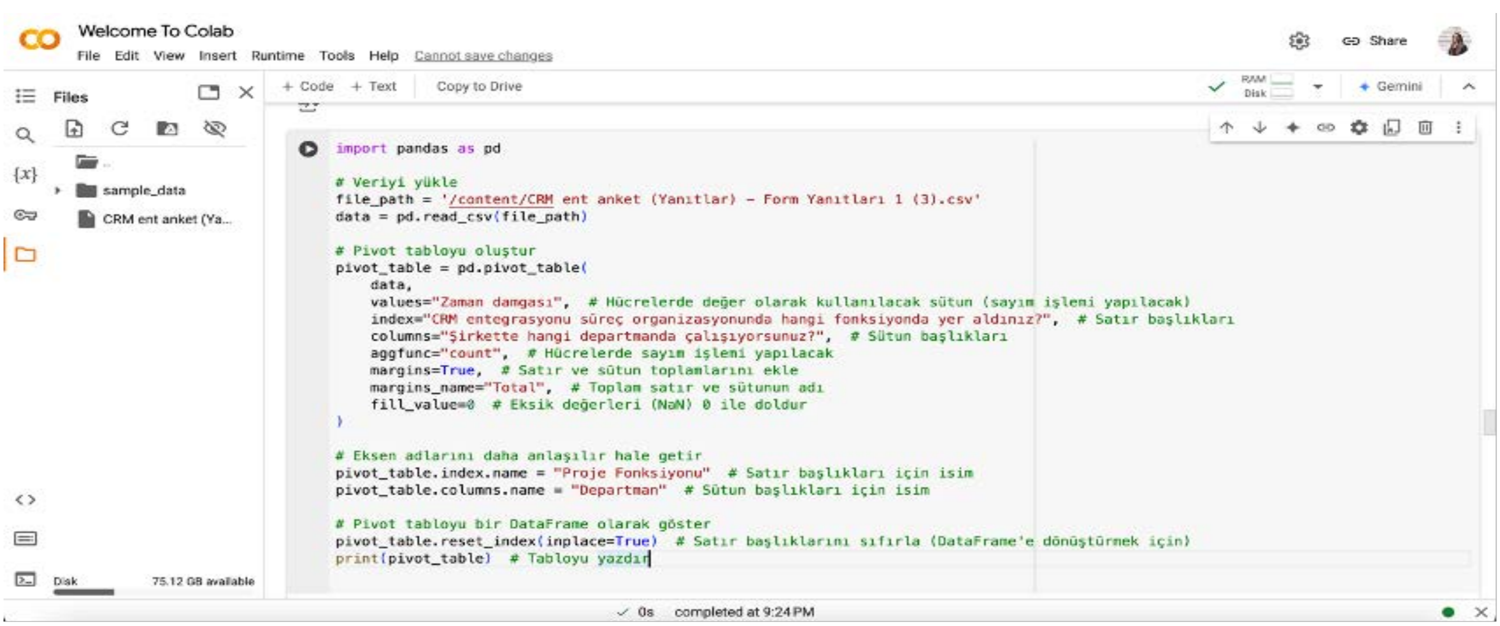
Initial Survey Data



The first two questions in the survey asked about demographic data, the department you work in the company, and the function of the project you are involved in. The answers to these questions were used to create a pivot table as in Figure 3.

Figure 3

Participant Demographic Distribution



According to the pivot table, the project's internally developed Sales/Support/Operations Management and Marketing/Business Development Management modules integrated as a third-party application tool are. The distribution of participants in these modules is shared in Table 2.

Table 2

Department and Project Function Distribution

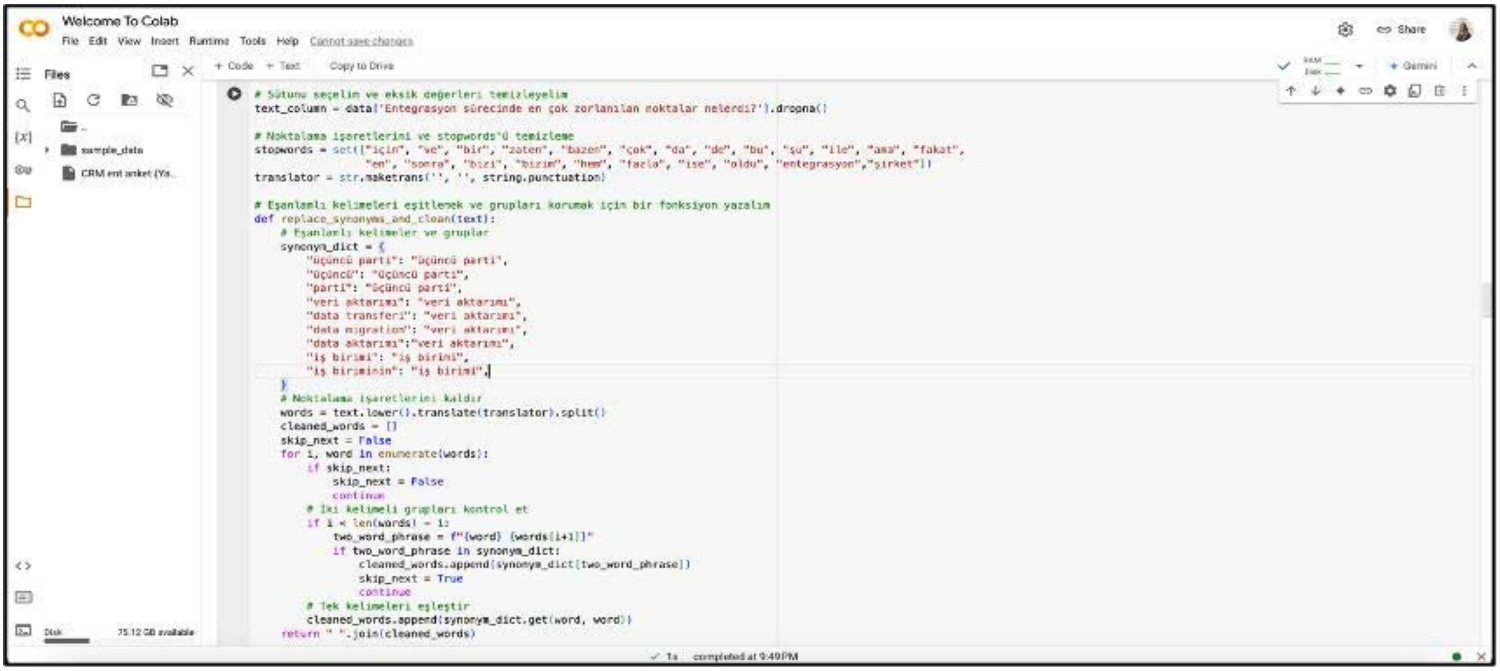
Project Function/Department	Information Technologies	Commercial Team	Product Management	Total
Marketing and Business Development		1		1
Sales, Support and Operations Management		1		1
I was involved in the entire project	2		2	4
Total	2	2	2	6

A total of 6 managers participated in the survey, including 2 people from Information Technologies 2, Commercial Team 2 and Product/Project Management. The project function distributions of these managers are as follows: While Product Management and Information Technologies managers took part in the entire project, one of the Commercial team managers took part in the Marketing module and the other in the Sales, Support and Operations module.

Within the scope of the third question, the open-ended responses of the participants regarding the difficulties they encountered in the CRM integration process were analyzed using the text mining method, as in Figure 4. These responses were converted into a word cloud, as in Figure 5, in order to identify frequently used words and expressions. The word cloud visualized the content of the participants' responses, making it easier to understand which points were emphasized more frequently.

Figure 4

Analysis of Difficult Points in the Process



While creating the word cloud, synonyms and words used together were defined, punctuation marks and words frequently used in Turkish such as prepositions and conjunctions were defined as stopwords and excluded from this analysis.

Figure 5

Difficult Points in the Process Word Cloud

The most frequently used expressions in word cloud analysis include:

- "Üçüncü parti"/Third party: Third party, Both technical and cultural adaptation issues when using third-party systems during the integration process constitute a significant part of the challenges. This expression illustrates the complexities of integrating outsourced solutions with in-house processes.
- "Veri aktarımı"/ Data transfer: Transferring data between different systems has been described as one of the most challenging stages of the process. Technical problems that arise during the transfer of large data sets, both from the old structure to the new structure and with third-party companies, have been frequently emphasized.
- "İş birimi"/Business unit: Participants stated that effective communication and coordination between business units were challenging elements during integration. These statements represent operational alignment and collaborative communication.

Within the scope of the fourth question, the advantages and disadvantages of the selected model, in which the internally developed structure and the third-party module are used together, were analyzed.

Figure 6

Advantages and Disadvantages Analysis

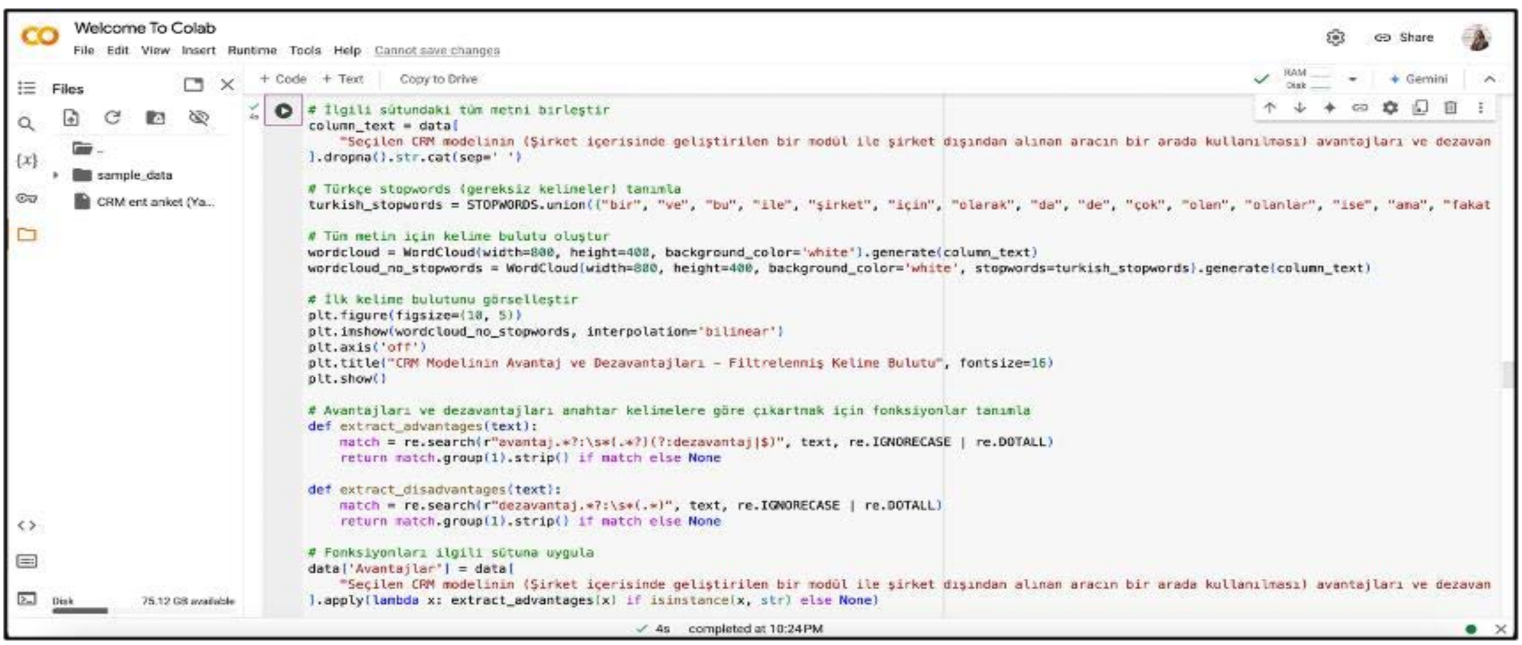


Figure 7

Disadvantages Word Cloud

As shown in Figure 7, the word cloud analysis of the selected model for disadvantages visualizes how users perceive the challenges in the CRM model. The prominent expressions are as follows;

- "Üçüncü partiye bağımlılık"/Third party dependency: Problems encountered in the integration process with externally sourced tools were among the most obvious difficulties. Especially in urgent cases, dependency on external companies led to delays in operational processes and disruptions in operation due to the fact that integration, maintenance and technical support processes were controlled by external sources.
- "Kültür farklılığı"/Cultural differences: Differences in communication and business practices between the company and third-party software providers have emerged as a significant challenge in the integration process.
- "Sınırlı yetkinlikler"/Limited capabilities: The limited capabilities of the third-party tool in some cases did not meet internal company needs or met them to a limited extent.

These findings illustrate the technical and organizational challenges experienced during the integration of the CRM model with outsourced tools.

Figure 8

Advantages Word Cloud

As shown in Figure 8, the following statements stood out regarding the advantages of the selected model;

- "Veri"/ Data: Due to the integration of data between systems, all data was collected in one place and this data enabled accurate targeting in communication scenarios. In addition, in the selected model, a portion of the data storage cost was loaded to the third party company.
- "Maliyet"/ Cost: In the selected model, purchasing some of the modules ready-made from outside provided a cost advantage while enabling the module to be put into use faster and easier.
- "Farklı kanallar"/Different channels: The advantage of being able to manage and measure all different communication channels from a single place stands out in the selected model.
- "Hedefleme"/Targeting: Since the data is collected in a single place thanks to the structure created, communication can be targeted in a more customized and personalized way using this data and can reach more accurate audiences.

In the fifth question, participant managers were asked what kind of differences they observed before and after integration and their open-ended responses were analyzed.

Figure 9

Before and After Differences Analysis

Figure 10

Before and After Differences Word Cloud

According to the analysis results, the following statements stand out;

- "Operasyonel ve manuel süreçler"/Operational and manual processes: One of the biggest words, "processes", emphasizes the effectiveness provided by CRM application by automating business processes. Operational effectiveness and making processes more efficient are among the important contributions of CRM integration to the business.

- “Tek platform”/Single platform; The prominence of the word “Platform” shows the ability of the CRM system to collect and organize business processes in a single center. With the CRM application, managing all data and operations through an integrated platform has made the processes more coordinated and effective.
- “Analiz”/Analysis: It reveals that one of the most important values that the CRM system provides to businesses is that it supports data-driven decision-making processes. Participants stated that thanks to CRM, data is analyzed faster and more accurately.
- “Zaman”/Time: The speed and time management improvements provided by the CRM application in business processes were frequently emphasized by the participants. CRM integration enabled faster completion of work by reducing and automating manual processes.

The sixth question asked about the contribution of the selected model to operational efficiency, again in an open-ended manner. The answers given to this question were analyzed.

Figure 11

Contribution Analysis to Operational Efficiency

Figure 12

Contribution to Operational Efficiency Word Cloud

According to the analysis results, the words “evet”/ yes, “hızlı”/ fast and “doğru”/correct stood out in the word cloud of the answers given to the question “Did the selected model contribute to operational efficiency? If so, in which areas?” as shown in Figure 12. The magnitude of the “evet”/yes and “doğru”/correct statements shows that the vast majority of participants agree that CRM makes a positive contribution to operational efficiency. The word “hız”/speed clearly shows the effect of CRM in accelerating business processes. CRM saved time by reducing manual processes and automated workflows. This enabled the business to respond to customer demands more quickly.

In the seventh and last question, managers were asked what the critical success factors of the CRM integration process were. The open-ended answers were analyzed using text mining.

Figure 13

Critical Success Factors Analysis

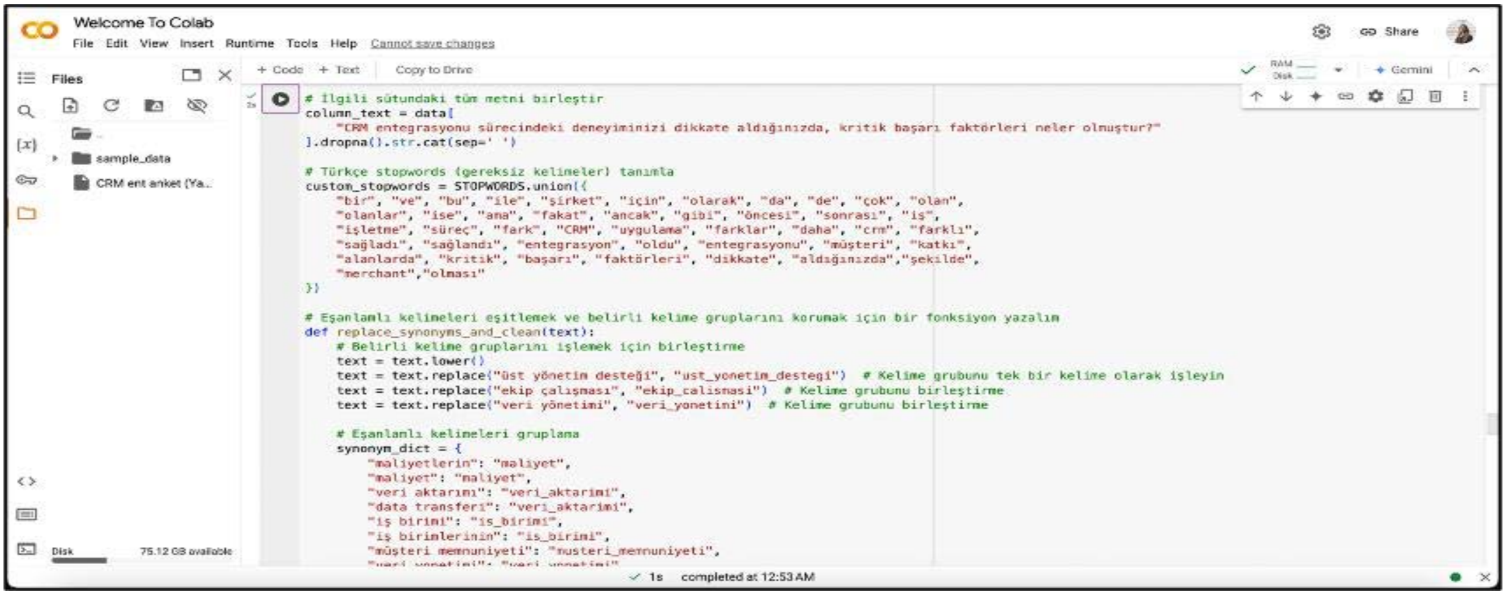


Figure 14

Critical Success Factors Word Cloud

This word cloud analysis visualized the critical success factors in the CRM integration process according to the participants' statements. This analysis aims to highlight the important elements that contribute to the success of the process by identifying the prominent themes in the integration process. As shown in Figure 14, the prominent words are as follows;

- "Üst yönetim desteği"/Top management support: One of the most striking phrases in the word cloud is "top management support." This phrase shows that the support and guidance received from top management plays a critical role in the success of the CRM integration process.
- "Veri"/Data: It shows that organizing, sharing and securely processing data is an important success factor in the integration process. During the CRM integration, the accuracy and consistency of data has emerged as one of the basic requirements for the effective operation of the system.
- "Tüm birimlerin sahiplenmesi"/Ownership of all units: The phrase "all units" emphasizes that CRM integration should not be limited to just one department, but that it is critical that all units across the company are included and owned. This increases coordination between teams throughout the process, ensuring that the system is implemented more effectively.
- The terms "Planlama"/planning and "geçiş"/transition indicate that CRM integration requires a detailed planning process and that it is important to implement it as quickly and as organized as possible. This finding indicates that executing the integration process with a good timeline is critical to success.

According to this analysis, it is seen that elements such as senior management support, data management, inter-unit participation, planning, employee ownership and effective communication play a key role in the success of the CRM integration process.

In the next section, findings will be shared through the analysis of the responses to all survey questions.

3.3. Findings

In this section, the research findings are grouped under five headings: difficulties experienced in the CRM integration process, advantages and disadvantages of using internal and external systems together, benefits of CRM integration, contribution of CRM integration to operational efficiency and critical success factors of the CRM integration process.

- Challenges in the integration process: In the survey results, the use of third-party tools, data transfer and communication between stakeholders were identified as prominent challenges. In particular, the importance of data transfer, third-party system compatibility and coordination between business units is emphasized. As stated in the literature, studies conducted by Fotouhiyehpour (2006) show how important cultural compatibility and situation analysis are for success.

- Advantages and disadvantages of using internal and external systems together: While third party dependency, limited competencies, cultural differences are prominent disadvantages, data importance, cost, management from a single source are prominent advantages. The advantages observed in business processes after CRM integration show that the system is an operational, strategic and customer-oriented transformation tool. These findings coincide with the need for integration preparation and cultural change emphasized by Almotairi (2009).
- Differences observed after CRM integration: Automated, single platform and data usage words stood out. This word cloud analysis visualizes many dimensions of the transformation provided by CRM application in business processes. Centralized management of data, rapid analysis and replacement of manual processes with automation are among the main benefits provided by CRM integration to business processes. In addition, the increase in personalized approaches in customer relations is another important contribution to increasing business performance. These findings show that CRM integration can be considered not only as a technological transformation but also as an improvement tool in operational, strategic and customer-focused processes.
- Contribution of CRM applications to operational efficiency: This word cloud analysis clearly reveals the contributions of CRM to operational efficiency. Participants particularly note the benefits provided in areas such as speed, automation, sales, marketing and analysis. Participants stated that CRM provides strategic and operational advantages to businesses by optimizing business processes. These findings show that CRM is not just a software solution, but also a technology that transforms the operational processes of businesses. The speed, automation and data focus offered by CRM contribute to businesses gaining a competitive advantage. It strongly supports the operational efficiency provided by its integration to business processes. In parallel with the strategic importance of CRM in organizational processes emphasized by Piskar and Faganel (2009) in the literature, participant responses also confirm the effectiveness of CRM in operational processes.

- CRM integration critical success factors: According to the survey results, it is seen that elements such as top management support, data management, inter-unit participation (Shum et al., 2008), planning, employee ownership and effective communication play a key role in process success. In the literature, the importance of top management support in critical success factors for CRM integration has been proven as a result of managerial interviews, as clearly stated by Sauer et al. (1997), Almotairi (2009), Ali et al. (2015), Ali et al. (2015), Mollaee et al. (2023) in chronological order.

  At the same time, the importance of data quality and data management has been proven, as identified by Almotairi (2009) and Widiantono and Sejati (2022).

  As Fotouhiyehpour (2006), Almotairi (2009) and Mollaee et al. (2023) stated, organizational culture, effective communication, participation of units and running towards a common goal have also emerged as critical success factors.

Considering all the findings, it has been observed that CRM is not only a technology integration but also requires the business processes and organizational culture to be made customer-oriented, as conveyed by Piskar and Faganel (2009), and it is much more than a technical process and creates organizational transformation in businesses. Factors such as top management support, cultural adaptation, data management and communication are key to success. Literature and field study findings show that CRM not only provides operational benefits to businesses but also offers strategic advantages.

4. Conclusion

The marketplace business model has a multi-layered and dynamic structure that brings together sellers and buyers. In this context, CRM solutions play a critical role in optimizing customer relationships and achieving the strategic goals of the business. The findings show that CRM not only ensures customer satisfaction, but also increases the capacity to manage processes within the business more efficiently and effectively.

Especially in the marketplace business model, CRM solutions are vital for managing the relationship between sellers and buyers and strategically directing these relationships. This study highlights the importance of these technologies in marketplace business models by revealing how CRM solutions help businesses gain competitive advantage.

Another important finding of the study is that CRM is not only a technology integration, but also how it plays a role in the strategic decision-making processes of the business. CRM enables businesses to adapt quickly to changes in the market and respond quickly and effectively to customer demands. The fact that CRM solutions strengthen customer relations and increase customer satisfaction will directly contribute to the long-term success of the company. In addition, CRM systems automate business processes and provide a more efficient workflow. This contributes to more efficient use of resources within the business and increased profitability of the business.

Implications for Practitioners

This study provides valuable insights for practitioners by revealing the critical role of CRM applications in the marketplace business model. Especially for businesses operating in the e-commerce sector, CRM solutions go beyond optimizing customer relations and become a tool that provides operational excellence. Practitioners can deduce from this study that CRM should not only be considered as a technological solution but also as a customer-focused strategic approach. It is emphasized that in order for CRM solutions to be successfully implemented, attention should be paid to elements such as strategic planning, correct data management, and the support of senior management and the entire organization working towards a common goal.

Implications for Academics

This study fills the gaps in the literature on CRM applications and makes significant contributions to the academic world. While the literature generally focuses on the operational processes and benefits of CRM, this study reveals the realized effects, critical success factors and challenges of CRM applications in marketplaces. In this respect, the study stands out as one of the rare studies examining the effects of CRM solutions in marketplace business models and is of a nature that will guide future academic research.

Limitations

This study deeply examines the impact of CRM solutions on the marketplace business model, but it has some limitations. The findings of the study are based on a specific e-commerce company and cannot be generalized to other marketplace models or different sectors. In addition, since the study is based on qualitative data, more comprehensive studies supported by quantitative data are necessary. Future research can evaluate the findings of this study from a broader perspective by examining the impacts of CRM applications on marketplace business models in different sectors. In addition, considering the lack of data on specific financial and labor dynamics in this study, integrating financial data and labor characteristics in future research will enable a more comprehensive and multidimensional analysis of the impacts of CRM solutions on the marketplace business model.

As a result, this study provides significant contributions to practitioners and the academic world with its findings such as the critical success factors and challenging points in the integration processes of CRM in e-commerce marketplaces.

References

Abdullah, S., Abdul Wahid, N., Abdul Razak, A. and Jan, M. 2024. "The influence of electronic customer relationship management (E-CRM) on customer satisfaction (CS) and customer loyalty (CL): A pilot study in malaysian private institute of higher learning," *Asian Journal Of Research In Business And Management, 6(2),* 58-70.

Al-Homery, HA, Ashari, H. and Ahmad, A. 2019. "The core components and types of CRM. *Pakistan Journal of Humanities and Social Sciences," 7(1),* 121 – 145.

Al-Homery, H.A., Ashari, H., and Ahmad, A. 2023. "Customer relationship management: a literature review approach," *International Journal of Global Optimization and Its Application* , *2(1),* 20-38.

Ali, Z., Ishaya, I. and Hassan, H. 2015. "The critical success factors of e-CRM implementation to small and medium enterprises," *International Conference on E-commerce.* Universiti Utara Malaysia, Malaysia. 58-62.

Almotairi, M. 2009. "A framework for successful CRM implementation," *In European and Mediterranean conference on information systems,* 1-12.

Annandhif, MAS, Sekarini Adhiati, MMRE and Rahardja, E. 2024. "A systematic literature review of the impact of artificial intelligence on customer relationship management and innovation," *Fakultas Ekonomi dan Bisnis UNTAN,* 321-326.

Armstrong, G., Adam, S., Denize, S., & Kotler, P. 2014. "*Principles of marketing,"* PearsonAustralia.

Buttle, F. and Maklan, S. 2019. "*Customer relationship management: concepts and technologies,"* Routledge.

Cahyani, DE, Rahmadani, D., Yunus, M., Pusawidjayanti, K., Nuradilla, S. and Aziz, SA 2023. "Development of e-commerce application using customer relationship management to increase the turnover of bendosewu farmers," *International Journal of Social Science Research and Review* , *6(4),* 201-210.

Cardoso, C. and Pacheco, J. 2024. "Leveraging social selling on LinkedIn for B2B relationship management in the COVID-19 Era," *on Humanities and Social Sciences* , 211.

Cătoiu, I., and Balaure, V. 1990. "Mutaţii în economia mondială şi reorientări în politica de piaţă a întreprinderilor," *Tribuna economică nr* , 15, 26.

Chen, I. J. and Popovich, K. 2003. "Understanding customer relationship management (CRM): People, process and technology," *Business process management journal* , *9(5),* 672-688.

Dyche, J. 2002. "*The CRM handbook: A business guide to customer relationship management,"* Addison-Wesley Professional.

Fotouhiyehpour, P. 2006. "*Assessing the readiness for implementing e-CRM in B2B markets using AHP method,"* (Unpublished master's thesis). Lulea University of Technology.

Garrido-Moreno, A., Padilla-Meléndez, A., & Del Águila-Obra, A. R. 2010. "Exploring the importance of knowledge management for CRM success," *International Journal of Industrial and Manufacturing Engineering, 4(6),* 629-633.

Grandhi, S. and Chugh, R. 2012. "Strategic Value of Mobile CRM Applications: A review of mobile CRM at dow corning and DirecTV," *International Proceedings of Computer Science and Information Technology* , *36(1),* 405-410.

Gupta, A. 2014. "E-commerce: role of e-Commerce in today's busines," *International Journal of Computing and Corporate Research, 4(1),* 1-8.

Høgevold, N., Rodríguez, R., Otero-Neira, C., and Svensson, G. 2024. "The role of digital communication technologies through customer and market knowledge in B2B on Sales Performance and Satisfaction," *Journal of Business-to-Business Marketing* , 1-21.

Kampani, N and Jhamb, D. 2020. "Analyzing the role of e-CRM in managing customer relations: a critical review of the literature," *Journal of Critical Reviews, 7(4),* 221-222.

Karagöl, Ö. 2007. "*Successful CRM application model building in telecom sector,"* (Unpublished master's thesis). Marmara University.

Kaur, H. 2024. "Elucidating the moderating role of CRM in business intelligence and organizational performance," *In Finance Analytics in Business: Perspectives on Enhancing Efficiency and Accuracy.* Doi: 10.1108/978-1-83753-572-920241012

Kawa, A. and Wałęsiak, M. 2019. "Marketplace as a key actor in e-commerce value networks," *LogForum, 15(4),* 521-529.

Kotler, P. 1996. "*Marketing Management–Analysis, planning, implementation and control-Prentice Hall* Inc. Inch," New Jersey, USA, 91-92.

Kotler, P., Brady, M., Goodman, M., and Hansen, T. 2019. "*Marketing management: european edition,"* Pearson Higher Ed.

Küpper, T., Jung, R., Lehmkuhl, T., Walther, S. and Wieneke, A. 2014. "Performance measures for social CRM: a literature review," *BLED 2014 Proceedings. 31* .

Lunn, M. 2002. “Using business models and revenue streams for digital marketplace success,” *Information management and computer security* , *10(1),* 20-27.

Marolt, M., Pucihar, A. and Zimmermann, H. D. 2015. “Social CRM adoption and its impact on performance outcomes: a literature review,” *Organizacija* , *48(4),* 260-271.

Mishra, A. and Mishra, D. 2009. “Customer relationship management: implementation process perspective,” *Acta Polytechnica Hungarica, 6(4),* 83-99.

Mollaee, N., Zanjirchi, S., Mirghafoori, S.H., and Zare, H. 2023. “Customer relationship management successful implementation in tourism industry*,” Journal of Tourism and Development* , *12(1),* 219-232. Doi: 10.22034/jtd.2022.327748.2564

Nicolau, A.I., Musetescu, A. and Mionel, O. 2014. “Stages in the evolution of marketing as a discipline,” *Knowledge Horizons Economics* , *6(2),* 166.

Ozay, D., Jahanbakht, M., Shoomal, A. and Wang, S. 2024. “*Artificial intelligence (AI)-based customer relationship management (CRM): a comprehensive bibliometric and systematic literature review with outlook on future research,”* Enterprise Information Systems. Doi: 10.1080/17517575.2024.2351869

Piskar, F. and Faganel, A. 2009. “A successful CRM implementation project in a service company: case study,” *Organizacija* , *42(5),* 199-208.

Purwoko, VI and Belgiawan, P.F. 2024. “Proposed marketing strategy and CRM for a parking technology company (case study: PT. Oranye),” *International Journal of Current Science Research and Review, 8(7),* 5941-5951.

Reinhold, O. and Alt, R. 2009. “*Enhancing collaborative CRM with mobile technologies,”* BLED 2009 Proceedings.

Rodriguez, M. and Boyer, S. 2020. “*The impact of mobile customer relationship management (mCRM) on sales collaboration and sales performance,”* J Market Anal 8, 137–148.

Shum, P., Bove, L. and Auh, S. 2008. “Employees' affective commitment to change: the key to successful CRM implementation,” *European Journal of Marketing* , *42(11),* 1346-1371. Doi: 10.1108/03090560810903709

Tamilia, R. D. 2009. “An overview of the history of marketing thought,” *Journal of Historical Research in Marketing*, *1(2),* 346-360.

Wahlberg, O., Strandberg, C., Sundberg, H., and Sandberg, C. 2009. “Trends, topics and under-researched areas in CRM research: a literature review,” *International Journal of Public Information Systems* , *2009(3),* 191-208.

Widiantono, A. and Sejati, P. 2022. “*Implementation of knowledge management on customer relationship management system, a literature review,”* Atlantis Press. Doi:10.2991/978-94-6463-084-8_7

Yasiukovich, S. and Haddara, M. 2021. “Social CRM in SMEs: a systematic literature review,” *Procedia Computer Science* , 181, 535-544. Doi: 10.1016/j.procs.2021.01.200

Yong, Z. 2024. “Digital marketing transformation strategies of traditional B2B for training and consulting enterprise,” *Science, Technology, and Social Sciences Procedia* , 2024(5).

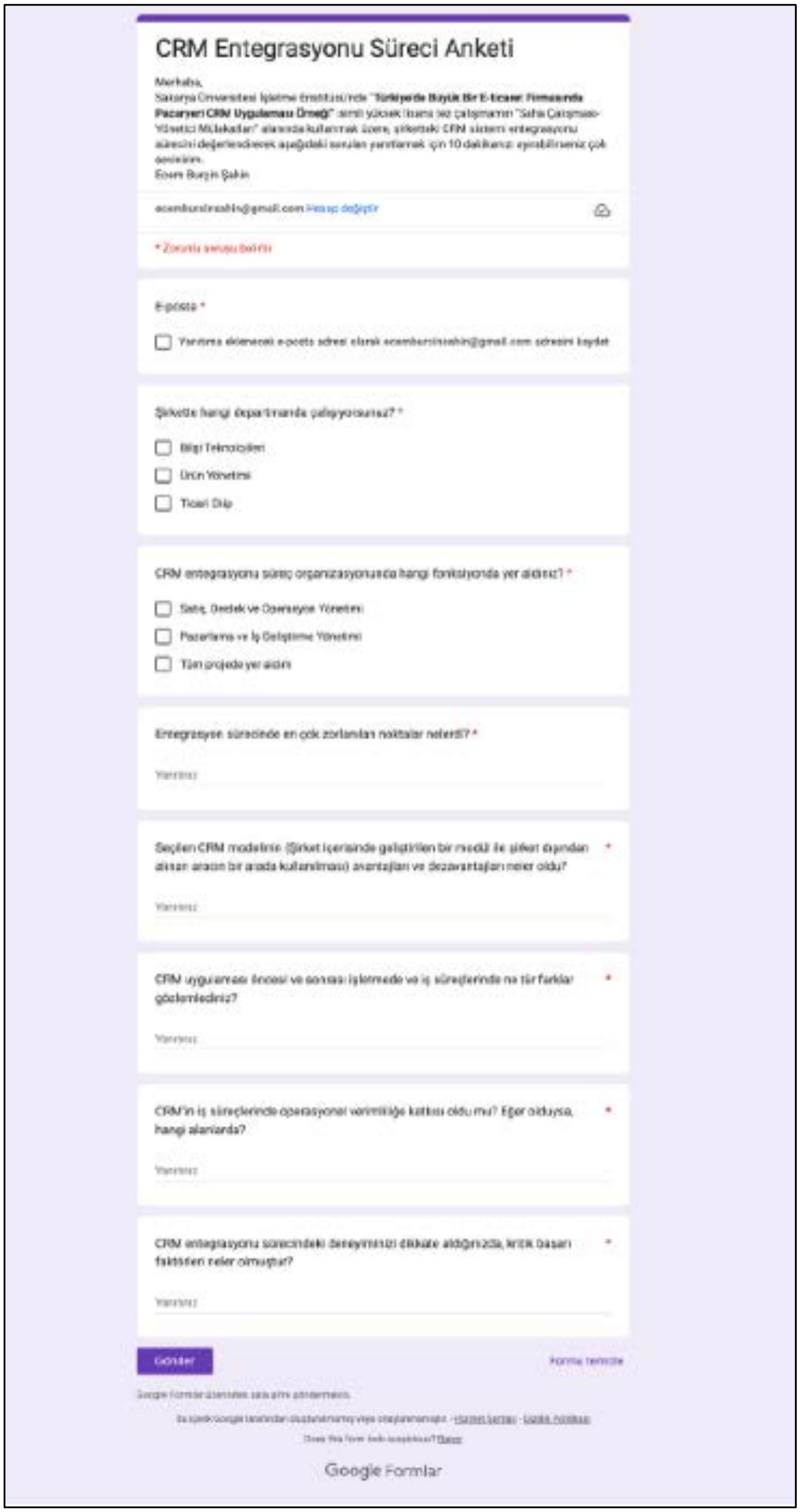
Zablah, AR, Bellenger, DN, & Johnston, W.J. 2004. “An evaluation of divergent perspectives on customer relationship management: Towards a common understanding of an emerging phenomenon,” *Industrial marketing management* , *33(6),* 475-489.

Zhang, L., Li, J., and Wang, Y. 2008.” Customer relationship management system framework design of Beijing Rural Commercial Bank,” *In 2008 IEEE International Conference on Service Operations and Logistics, and Informatics, 1(1),* 97-101.

Ziky, R., Bahida, H., Abriane, A. and Elkotbi, M. 2024. “Social CRM and customer relationship performance: a bibliometric analysis of literature,” *Repères et Perspectives Economiques* , *8(1).* Doi: 10.34874/PRSM.RPE.48301

Zulyanti, NR and Irawan, MRN 2023. "Customer relationship management: literature review," *International Journal of Science, Technology & Management* , *4(4),* 884-892.

Appendix-1. Manager Interview Questionnaire



CRM Entegrasyonu Süreci Anketi

Merhaba,
Sakarya Üniversitesi İşletme Enstitüsü'nde "**Türkiye'de Büyük Bir E-ticaret Firmasında Pazaryeri CRM Uygulaması Örneği**" isimli yüksek lisans tez çalışmamın "Saha Çalışması-Yönetici Mülakatları" alanında kullanmak üzere, şirketteki CRM sistemi entegrasyonu sürecini değerlendirerek aşağıdaki soruları yanıtlamak için 10 dakikanızı ayırabilirseniz çok sevinirim.
Esem Burçin Şahin

Hesap değiştir

* Zorunlu soruyu belirtir

E-posta *

- [ ] Yanıtıma eklenecek e-posta adresi olarak ... adresini kaydet

Şirkette hangi departmanda çalışıyorsunuz? *

- [ ] Bilgi Teknolojileri
- [ ] Ürün Yönetimi
- [ ] Ticari Dijital

CRM entegrasyonu süreç organizasyonunda hangi fonksiyonda yer aldınız? *

- [ ] Satış, Destek ve Operasyon Yönetimi
- [ ] Pazarlama ve İş Geliştirme Yönetimi
- [ ] Tüm projede yer aldım

Entegrasyon sürecinde en çok zorlanılan noktalar nelerdi? *

Yanıtınız

Seçilen CRM modelinin (Şirket içerisinde geliştirilen bir modül ile şirket dışından alınan aracın bir arada kullanılması) avantajları ve dezavantajları neler oldu? *

Yanıtınız

CRM uygulaması öncesi ve sonrası işletmede ve iş süreçlerinde ne tür farklar gözlemlediniz? *

Yanıtınız

CRM'in iş süreçlerinde operasyonel verimliliğe katkısı oldu mu? Eğer olduysa, hangi alanlarda? *

Yanıtınız

CRM entegrasyonu sürecindeki deneyiminizi dikkate aldığınızda, kritik başarı faktörleri neler olmuştur? *

Yanıtınız

Gönder

Formu temizle

Google Formlar

Paper #22

Title: Minimizing Total Tardiness in Flowshops with Uncertain Setup Times

Author(s): Ali Allahverdi (Gazi University, Turkey), Muberra Allahverdi (Ankara Yıldırım Beyazıt University, Turkey)

Abstract:
This paper addresses the two-machine flowshop scheduling problem with uncertain setup times bounded by known limits. To minimize total tardiness, the authors propose two heuristic algorithms and compare them to the earliest due date (EDD) method. Computational experiments show that one heuristic reduces the error by a factor of 6.5, and the other by a factor of 8, with improved performance consistency as problem size increases.

Keywords: Flowshop, Total Tardiness, Uncertain Setup Times, Scheduling, Heuristic Algorithms

Paper #11

Title: Classification of the Same Line Downtime Reasons Defined by Different Handwritings Using Artificial Intelligence Techniques

Author(s): Ayşegül Aydın, Tijen Över Özçelik, Serap Çakar Kaman

Affiliations:
- Sakarya University, Industrial Engineering Department
- Sakarya University, Computer Engineering Department

Abstract:
This study examines the application of AI techniques to classify handwritten records of production line downtime submitted by various operators. Due to inconsistent descriptions resulting from language variation and a lack of standardized codes, the research aims to identify effective classification methods using scanned data and optical character recognition. It evaluates various AI techniques based on a three-month dataset and proposes a software approach to calculate line efficiency based on recognized text.

Keywords: Handwriting Recognition, Natural Language Processing, AI Techniques, Classification, Python.

Paper #19

Title: The Spread of Conspiracy Theories on Social Media: Emotion Analysis and the Dynamics of Fear, Suspicion, and Insecurity

Author(s): Dr. Öğr. Üyesi Fatih Çallı and Emel Koçyiğit (Sakarya University)

Abstract:
This study examines how emotions such as fear, suspicion, and insecurity influence the dissemination of conspiracy theories on social media. Using sentiment analysis, natural language processing (NLP), and machine learning algorithms, the research analyzes emotional reactions in online posts to assess their impact on social trust and public perception. The findings aim to support the development of strategies for managing negative emotions and reducing social polarization.

Keywords: Conspiracy Theories, Social Media, Emotion Analysis, Fear, Machine Learning, NLP

THE SPREAD OF CONSPIRACY THEORIES ON SOCIAL MEDIA: EMOTION ANALYSIS AND THE DYNAMICS OF FEAR, SUSPICION AND INSECURITY

Dr.Öğr.Üyesi Fatih ÇALLI

Emel KOÇYİĞİT

Sakarya Üniversitesi (Bilgisayar ve Bilişim Bilimleri Fakültesi, Bilişim Sistemleri ve Teknolojileri Bölümü),

fcalli@ogr.sakarya.edu.tr

Sakarya Üniversitesi (Fen Bilimleri Enstitüsü, Bilişim Sistemleri Mühendisliği),

emel.kocyigit@ogr.sakarya.edu.tr

SUMMARY

By analyzing the emotional states expressed by users on social media platforms, to examine how emotions such as fear and insecurity are reflected at the social level aims. Social media is important in the way individuals disseminate their thoughts and feelings.While the negative sentiments spread through these platforms have an impact on social perception and The effects of social media on behavior are attracting more and more attention.In this research, sentiment analysis methods are used to analyze social will focus on expressions of fear and insecurity in media posts. Natural language processing (NLP) and machine learning techniques will be used to analyze text data; in this process, data to be collected from social media platforms (such as Twitter, Facebook), keywords and emotion labeling algorithms.

Data collection process This process can be collected in the form of Api service, manual data sets, etc. and filtering content that expresses certain emotions, such as insecurity will be realized. The collected data will be analyzed using machine learning algorithms (Naive Bayes, SVM, LSTM, etc.) and analyzed. In the process of analysis, these emotions distribution in specific social and cultural contexts and what factors trigger these emotions will be investigated. As a result, it will be analyzed how feelings of fear and insecurity in social media affect social psychology. and what kind of an impact it has on individuals. The resulting The findings are important in improving social trust and managing negative emotions. will contribute to the development of potential strategies.

Research Purpose and Scope:

To understand the emotional reactions (fear, suspicion and distrust) of users to conspiracy theories spread on social media platforms. Using artificial intelligence (AI)-based sentiment analysis, we aim to examine the effects of conspiracy theories on social media in detail and to reveal the role of these emotional states in the spread of theories. The rapid spread of belief in untruths will be analyzed by algorithms and the rates of negative effects of people in the face of this news will be determined by algorithms. The emotional components of conspiracy theories will help to understand why and how these theories reach large masses and how they can deepen social polarization.

Method and Data Collection:

In this thesis, sentiment analysis methods will be applied on texts and content shared on social media platforms. Natural language processing (NLP) techniques and sentiment analysis software will be used for data analysis.

Paper #45

Title: The Effect of Social Media Addiction on Students’ General Academic Success and Focus

Author(s): Büşra Alma Çallı and Meryem Nur Baran (Sakarya University)

Abstract:
This study investigates the relationship between social media addiction, academic success, and focus among university students. Based on a sample of 226 students from Sakarya University and Sakarya University of Applied Sciences, the research applies validated scales to assess addiction, focus, and achievement levels. The findings reveal a positive but non-causal correlation between social media addiction and academic success, and a statistically insignificant correlation with focus. The results suggest that while digital platforms can support learning, excessive use may present complex effects on students’ academic performance and concentration.

Keywords: Social Media Addiction, Academic Success, Focus, University Students, Behavioral Dependency

INTRODUCTION

The rapid spread of the internet and the fact that digital platforms have become an inseparable part of daily life have deeply affected the way individuals access information, their social relationships and their living habits. Social media networks such as Facebook, Instagram, Twitter, Linkedin , Youtube and Tumblr, which have entered our lives and are quite popular, have been used by many people in the world and in Turkey for a long time (Çiftçi, 2018). The widespread use of social media in particular shapes individuals' lifestyles, mindsets and time management beyond communicating and sharing information. However, the impact of this transformation, especially on young individuals, is open to debate. For individuals with intense academic responsibilities, such as university students, social media use has the potential to directly affect their study routines and ability to focus. On the other hand, increasing the time spent on social media can lead to decreased productivity, decreased motivation for lessons and a decline in academic success in the long term. This situation reveals the need for a balanced use between the opportunities provided by technology and individual responsibility. Social media is a tool that students can use to support their education, but when used excessively, it can increase distraction and hinder an efficient learning process. In today's world, this critical relationship between social media addiction and academic success has become an important issue to examine.

Social media applications eliminate various limitations and provide individuals with the opportunity to facilitate communication and access information. The young generation's preoccupation with social media has made them unable to resist social media as an alternative to cope with anxiety and stress. This situation, in addition to the positive features of social media, also leads to some problems, one of which is social media addiction.

Social media addiction is a type of behavioral dependency in which an individual uses social media platforms in an uncontrolled and excessive manner, disrupting their daily, academic and professional responsibilities, and negatively affecting their social characteristics. This addiction manifests itself in the form of restlessness, anxiety and stress when the individual is prevented from accessing social media, constantly feeling the need to check notifications and tending to the virtual world rather than real-life transactions.

Excessive use and lack of control are the main causes of social media addiction or behavioral addiction disorder, which leads to social overload, jealousy and anxiety, similar to compulsive buying . Mood swings, negative consequences and excessive time spent on social media cause feelings of loss of productivity and isolation that develop over time with psychological dependence on social media, which leads users to try to overcome their unwanted moods by using social media (Aslan and Yaşar 2020; Odacı 2013; Sanchez, Cisneros , Barja , Munive , Mayta 2023).

The fact that social media has become addictive for users brings with it some problems. Face-to-face meetings have been replaced by virtual environments. Studies have also shown that social media addiction causes wasted time and this leads to academic failure. (Cabral , 2011; Menayes , 2015; Kırık et al., 2015; Hawi and Samaha , 2017).

Social media addiction can have negative effects on students' academic success. Constant notifications and attention directed to content can make it difficult for students to focus on their studies, reducing their productivity. It also causes them to distance themselves from the classroom environment. Spending time on social media for long periods of time, especially sharing and interacting late at night, disrupts sleep patterns and increases mental fatigue. This can negatively affect participation in classes and exam preparation. In addition, time spent on social media can prevent students from engaging in extracurricular activities and establishing face-to-face social relationships, which negatively affects overall personal development and therefore academic success.

Academic success is not only about getting high grades, but also about developing the ability to access, understand and apply information. Achieving this success at the undergraduate level is possible with disciplined work, effective time management and critical thinking skills. The student's passion for learning, the habit of using the right resources and the ability to cope with the challenges they encounter are the cornerstones of their academic journey.

The purpose of this research is to examine the relationship between university students' social media addiction and their general academic success. It is also aimed to reveal whether variables such as students' gender, the social media platform they use most, and the time they spend on social media create differences in students' opinions on the subject.

METHOD

In this study, which aims to examine the social media addiction levels of university students in terms of general academic success and also their focus, the sample group consists of undergraduate and associate degree students including 60 departments at Sakarya University and Sakarya University of Applied Sciences. The 7-question survey prepared by Çömlekçi and

Başol (2019) was used to measure the social media addiction levels of the participants. A 17-question survey prepared by Orçanlı , Bekmezci , and Boztoprak (2021) and 3 questions about focus was used to measure the general academic success of the students. In addition to the social media addiction level, general academic success, and focus scales, the students were also asked about socio-demographic information, the time they spent on social media, and information about the social media platform they use the most. The study group consists of 226 students, including a total of 60 students from undergraduate and associate degree departments studying at Sakarya University and Sakarya University of Applied Sciences in the 2024-2025 academic year. In order for the study to yield more reliable results, 226 survey forms were evaluated by removing the forms that were filled in incompletely or incorrectly from the applied survey form. An attempt was made to obtain a general average by taking the averages of the survey forms taken into consideration for each section per question. The correlation value between the sections was calculated with the obtained general average, and the separate reliabilities of the social media addiction scale, general academic success scale and focus scale were calculated.

FINDINGS

When Table 1, which summarizes the socio-demographic characteristics of the students participating in the survey, is examined, it is observed that 62.8% of the participants are female and 37.2% are male. According to the information in Table 2, 81.8% of the students participating in the study are studying in the humanities (social) sciences and 18.2% in science. The reason for the proportional difference in the number of students between the sciences is that the survey forms delivered are more accessible at Sakarya University. When we examine the social media platform used the most by the students participating in the study in Table 3, Instagram is 76.1%, while LinkedIn is the least used social media platform with 0.9%. When we examine the time spent on social media in Table 4, while the rate of students using social media for 3-4 hours is 46.0%, the rate of those using it for less than 1 hour is 7.5%.

Table 1- Demographic Distributions

	SCORE	FREQUENCY
Male	84	37.2
Woman	142	62.8
Total	226	100

Table 2- Distribution Table of Students in Humanities and Sciences

HUMAN (SOCIAL) SCIENCES		SCIENCE	
Coaching	0.4	Emergency Aid and Disaster Management	0.4
Banking and Insurance	0.4	Computer Engineering	0.9
Printing house	0.4	Information Systems Engineering	0.4
Labor Economics and Industrial Relations	0.9	Biology	0.4
Econometrics	0.4	Biomedical Engineering	0.4
Science Teaching	0.9	Bioengineering	0.4
Photography and Videography	0.4	Electrical Electronics Engineering	1.3
Gastronomy and Culinary Arts	4.0	Industrial Engineering	0.4
Visual Communication Design	1.8	Physiotherapy	0.4
Law	3.5	Physiotherapy	2.2
Economy	0.4	Nursing	0.4
First and Emergency Aid	0.4	Building	0.4
Human Resources Management	13.3	Control and Automation Engineering	0.4
Occupational Health and Safety	0.9	Mechanical Technician	0.4
Business	17.7	Maths	0.4
Finance	0.4	Metallurgical and Materials Engineering	0.4
Special Education Teaching	0.4	Landscape Architecture	0.4
Retail Sales and Store Management	6.6	Digital	0.4
Psychology	1.3	Civil aviation	0.4
Recreation	1.8	Aquaculture Engineering	0.4
Health Management	1.8	Design	0.4
Politics	0.4	Medical Laboratory Techniques	1.3
Political Science and Public Administration	1.8	Faculty of Medicine	0.4
Social work	1.3	Software	0.4
Sociology	0.4	Midwifery	0.9
Sports Management	0.4	Web Design	0.4
Tourism Management	0.4	Elderly Care	0.9
Management Information Systems	8.4		
Tourism Guidance	0.9		
International Trade and Logistics	9.7		
TOTAL	**81.8**	**TOTAL**	**18.2**

Table 3- Social Media Platforms Used

	SCORE	FREQUENCY
Other	24	10.6
Facebook	6	2.7
Instagram	172	76.1
LinkedIn	2	0.9
X(Twitter)	22	9.7

Total	226	100.0

Table 4- Time Spent on Social Media

	SCORE	FREQUENCY
Less than 1 hour	17	7.5
1-2 hours	56	24.8
3-4 hours	104	46.0
5-6 hours	49	21.7
Total	226	100.0

Table 4 shows the distribution of time spent on social media platforms used by students. The rate of time spent by students on social media platforms was determined as "less than 1 hour" 7.5%, "1-2 hours" 24.8%, "3-4 hours" 46%, "5-6 hours" 21.7%. When we look at the results in Table 4, the time spent with "3-4 hours" was determined as 46%, and this rate shows that students spend a significant amount of time on social media during the day and that there is a serious addiction to different social media platforms.

Table 5- Average Responses to Social Media Addiction Scale Questions

1. I have problems with my family because of my use of social media.	1.80
2. My interest in other activities (sports, reading, etc.) decreases because of my use of social media.	2.54
3. I neglect my home/work/school responsibilities because of my use of social media.	2.13
4. I spend less time with my family because of my use of social media.	2.19
5. I spend less time with my friends because of my use of social media.	1.87
6. People around me complain about the time I spend on social media.	1.78
7. I can't get away from social media even if my friends invite me.	1.38
TOTAL	**1.96**

Table 6- Average Responses to Focus Scale Questions

1. It was very easy to keep myself from getting lost in my studies this year.	2.25
2. I had no difficulty concentrating on lessons this year.	2.81
3. This year my attention was diverted very quickly in lessons.	2.83
TOTAL	**2.63**

Table 7- Average Responses to General Academic Success Scale Questions

1. I followed a good study schedule this year.	2.64
2. I worked really hard this year.	2.65
3. I tried everything I could to be successful this year.	2.62
4. I worked hard this year.	2.56
5. I think I used my studying skills very well this year.	2.66

6. I studied very hard this year because I wanted to understand this year's topics.	2.57
7. I was very good at homework this year.	2.31
8. I used the goal-setting strategy this year.	2.50
9. I am well prepared.	2.44
10. I studied hard to prove that I could get a good grade.	2.52
11. I used planning tools such as agendas and calendars very well this year.	2.99
12. I studied the right topics while preparing for the exams this year.	2.25
13. I am very pleased to learn new topics this year.	2.12
14. This year I enjoyed the challenge of learning just for the sake of learning.	2.61
15. I was pretty sure my grades would be good this year.	2.38
16. I had to get good grades this year to maintain my GPA.	1.91
17. I had a hard time concentrating on my studies this year.	2.81
TOTAL	**2.50**

When we examine the information in Tables 5, 6 and 7, we see that Table 5 includes the average responses to the social media addiction scale, Table 6 includes the average responses to focus, and Table 7 includes the average responses to the general academic success scale, and these averages then help us measure the correlation.

Table 8- Measuring the relationship between social media addiction, general academic achievement, and focus

		Social Media Addiction Scale	General Academic Success Scale	Focus Scale
Social Media Addiction Scale	Pearson Correlation	1	,763 *	,822
	Sig. (2-tailed)		**,046**	**,386**
	N	7	7	3
General Academic Success Scale	Pearson Correlation	,763 *	1	,500
	Sig. (2-tailed)	**,046**		**,667**
	N	7	17	3
Focus Scale	Pearson Correlation	,822	,500	1
	Sig. (2-tailed)	**,386**	**, 667**	
	N	3	3	3

According to the findings in Table 8, there is **a positive and significant relationship between social media addiction and general academic success** . This suggests that social media addiction may increase with academic success. However, since the correlation does not indicate causality, it is difficult to say that this relationship represents a direct effect. Although the literature suggests that social media addiction generally has a negative effect on academic success, *a positive relationship* was found in this study. This result may be due to various factors such as social media facilitating access to academic resources, students benefiting from digital learning environments, or the intervention of different individual variables. However, there is **a positive correlation between social media addiction and focus** . However, since the significance level of this relationship is **$p>0.05$,** it cannot be considered statistically significant. This result indicates that the level of focus may also increase as social media addiction increases. Although there are findings in the literature that social media addiction negatively affects focus, a positive relationship was observed in this study. However , there is **a positive correlation between academic success and focus** . However, since the significance level of this relationship is **$p>0.05$** , it is not considered statistically significant. This suggests that there may be a certain relationship between academic achievement and focus, but it does not form a strong bond. In other words, it can be said that as students' focus levels increase, their academic achievement tends to increase, but more data and analysis are needed to understand whether this interaction is coincidental.

Table 9- Social Media Addiction Scale Cronbach Alpha Value

Cronbach's Alpha	N of Items
,856	7

obtained value of **$\alpha=0.856$** reveals that the internal consistency of the scale is high and the scale items provide consistent measurements with each other. This result shows that the Social Media Addiction Scale is a reliable measurement tool and can measure the evaluated variable systematically.

Table 10- General Academic Success Scale Cronbach Alpha Value

Cronbach's Alpha	N of Items
,936	17

The Cronbach's Alpha ($\alpha=0.936$) value in Table 10 shows that the General Academic Success Scale is a highly reliable measurement tool and can be used safely in assessing academic success. In this context, it shows that the scale items are highly consistent and reliably assess the academic success variable we measure.

Table 11- Focus Scale Cronbach Alpha Value

Cronbach's Alpha	N of Items
,195	3

The Cronbach's Alpha (α=0.195) value in the table **shows that the internal consistency of the Focus scale is extremely low.** In this context, it is seen that the scale items show a weak correlation with each other and the scale is insufficient to measure the focus variable reliably.

CONCLUSION

In this study, the social media addiction levels of university students who make up the segment that uses social media intensively and the focus of this addiction level on the general academic success of the students were investigated. The sample group of the study consisted of 226 students, 60 of whom were undergraduate and associate degree students studying at Sakarya University and Sakarya University of Applied Sciences. The vast majority of the students participating in the study stated that they used social media for 3-4 hours and chose Instagram as the application they spent the most time on. The Cronbach alpha value (0.865) measured in the first 7-question social media addiction questionnaire directed to the students revealed that it was a reliable measurement tool and that there was a positive relationship between the general academic success of the students as social media addiction increased. In another 17-question general academic success questionnaire directed to the students, it was concluded that the measurement tool was reliable and that there was a positive relationship. Our last questionnaire directed to the students, which was a 3-question questionnaire, revealed that the consistency was low and the items showed weak reliability within themselves.

References

- Al- Menayes , J. J. (2015). Dimensions of social media addiction among university students in Kuwait . Psychology and Behavioral Sciences . 4(1). 23-28.
- Aslan İ., Yaşar ME Measuring social media addiction among university students. Int J Contemp Eco My name Sci . (2020) 13:340-8.
- Aslan I., Polat H. (2024). Investigation of social media addiction among university students and the effects of social media addiction, loneliness, depression, life satisfaction and problem solving skills on academic self-efficacy and academic success. Frontiers in Public Health . Original Research Article 12.
- Baz, F. Ç. (2018). Social Media Addiction: A Study on University Students. International Journal of Social Research. 9(16).
- Cabral , J. (2011). Is generation y addicted to social media . The Elon Journal of Undergraduate Research in Communications. 2(1). 5-14.
- Çiftçi, H. (2018). Social media addiction among university students. MANAS Journal of Social Research. 7(4).
- Hawi , N. S. , & Samaha , M. (2017). the relations among social media addiction , self-esteem , and life satisfaction in university students . Social Science Computer Review , 35(5). 576-586.
- Kirik, AM, Arslan, A., Cetinkaya, A., & Gul, M. (2015). A quantitative research on the level of social media addiction among young people in Turkey . International Journal of Science Culture and Sport (IntJSCS), 3(3). 108-122.
- Odacı H. Risk taking behavior and academic self-efficacy as variables in problematic internet use among adolescent university students. Child Youth Serv Rev. (2013) 35:183-7.
- Sanchez-del Hierro MP, Cisneros-Burga J, Barja-Ore J, Munive-Degregori A, MaytaTovalino F. Bibliometric analysis of the impact of social network addiction on worldwide scientific production and collaboration during the COVID-19 pandemic. Natl J Community Med . (2023) 14: 800-6.

Scale Resources

- Orçanlı K., Bekmezci M., Boztoprak H. (2021). Adaptation of Academic Success Inventory Scale for College Students to English : Validity and Reliability Study . International Journal of Social Research. 17(37). 1-28.

- Çömlekçi MF, Başol O. (2019). Investigation of the Relationship between Social Media Usage Purposes of Young People and Social Media Addiction. Celal Bayar University Journal of Social Sciences. 17(4). 173-188.

Paper #25

Title: Applications of Artificial Intelligence and Machine Learning in Edge Devices to Optimize Digital Carbon Footprint

Author(s): Çağlar Şimşek and Fatih Çallı (Sakarya University)

Abstract:
This study investigates the use of AI and machine learning on IoT edge devices to reduce energy consumption and digital carbon footprint. It compares deep learning models (e.g., MobileNetV2, ResNet18) across various hardware platforms, assessing their performance in terms of latency, accuracy, and energy use. Optimization techniques such as pruning and quantization are also applied. Results show that these models can improve energy efficiency while maintaining performance, offering a strategic framework for sustainable AI deployment in smart environments.

Keywords: Artificial Intelligence, Deep Learning, Carbon Footprint, Energy Efficiency, IoT, Model Optimization, Quantization, Pruning, Knowledge Distillation

Paper #59

Title: Digital Student Services: Intelligent Chatbot Systems Supported by Artificial Intelligence and RAG Model

Author(s): Semih Ceyhan, Musab Talha Akpinar and Muhammed Fatih Özer

Abstract:
This paper presents the design and evaluation of a student services chatbot powered by Large Language Models (LLMs) and Retrieval-Augmented Generation (RAG). Deployed in a university context, the chatbot enhances response accuracy and accessibility by retrieving real-time institutional data. Through pre- and post-deployment evaluations, the system demonstrates improved efficiency, usability, and student satisfaction, contributing to the digital transformation of higher education services.

Keywords: Artificial Intelligence, Chatbots, RAG Model, Student Services, Higher Education, LLMs

DIGITAL STUDENT SERVICES: INTELLIGENT CHATBOT SYSTEMS SUPPORTED BY ARTIFICIAL INTELLIGENCE AND RAG MODEL

ABSTRACT

The integration of digitalization and Artificial Intelligence in higher education has transformed student services, necessitating intelligent and responsive solutions. Traditional administrative processes often face inefficiencies and delays, leading to student dissatisfaction. AI-driven chatbots powered by Large Language Models (LLMs) and Natural Language Processing (NLP) offer a promising alternative, yet conventional rule-based models lack real-time adaptability. This study develops a chatbot using the Retrieval-Augmented Generation (RAG) model, enhancing response accuracy through real-time information retrieval. Initial interviews with 20 students guided the chatbot's design, while post-deployment evaluation with 40 students assessed response quality, reliability, and usability. Integrated into the university's student affairs portal and mobile application, the chatbot improves service accessibility and student engagement. Findings suggest enhanced accuracy, efficiency, and user satisfaction, contributing to the digital transformation of university services and demonstrating the potential of AI-driven chatbots in higher education.

Keywords: Artificial Intelligence, Large Language Models, Retrieval-Augmented Generation,

1 INTRODUCTION

The rapid advancement of digitalization and AI has transformed higher education, necessitating the development of intelligent and adaptive solutions to enhance student services. Traditional university administrative processes are often hindered by inefficiencies, delays, and limited accessibility, impeding students' ability to obtain timely and accurate information. AI-powered chatbots LLMs and NLP have emerged as a promising alternative, enabling automated, interactive, and scalable service delivery (Hadi and et al, 2023). However, conventional rule-based and static chatbot systems are inherently constrained by predefined datasets, resulting in outdated or contextually inadequate responses that fail to address evolving student needs (Izadi & Forouzanfar, 2024). To overcome these limitations, this study proposes an AI-driven chatbot system based on the RAG model, which combines real-time knowledge retrieval with generative AI capabilities. Unlike static models that rely solely on pre-trained linguistic patterns, RAG dynamically accesses external databases, ensuring accurate, up-to-date, and contextually relevant responses to student inquiries. This approach significantly enhances chatbot adaptability, reducing reliance on static datasets while improving responsiveness and reliability (Jurafsky, D., & Martin, J. H. (2024).

Various techniques in LLM optimization serve distinct purposes in AI-driven applications (Alto, 2024). Fine-tuning allows models to specialize in specific domains, whereas prompt engineering refines output quality without additional training. Few-shot and zero-shot learning facilitate adaptability in novel tasks with minimal labeled data, while reinforcement learning from human feedback (RLHF) enhances model reliability and ethical alignment (Sarkar, 2025). Model distillation reduces computational demands by transferring knowledge from complex architectures to lightweight models, and the Mixture of Experts (MoE) framework optimizes efficiency through specialized sub-models. Empirical studies underscore the efficacy of LLM-enhanced chatbots. Chen et al. (2024) reported a 94.7% accuracy rate for a GPT-3.5-based chatbot in university admissions, while Olawore et al. (2024) demonstrated the superior performance of retrieval-augmented models over standalone LLMs. Despite these advancements, LLMs remain opaque "black box" systems, posing challenges in explainability, bias mitigation, and hallucination (misleading information generation). Addressing these concerns requires robust evaluation frameworks to ensure AI-driven chatbots are transparent, ethical, and contextually precise (Zhao et al., 2024).

This study develops and evaluates a RAG-based chatbot for university student affairs, deployed in a pilot university in Turkey. Through interaction logs and user satisfaction surveys, the research assesses its effectiveness in enhancing student engagement, accessibility, and administrative efficiency, contributing to the broader digital transformation of higher education services.

2 CONCEPTUAL FRAMEWORKS

The evolution of AI has been driven by the development and assessment of increasingly sophisticated models. The evaluation of AI systems plays a crucial role in identifying their limitations and improving their performance, ultimately leading to the creation of more robust and reliable models (Sarker, 2022). In recent years, LLMs have garnered significant attention across academic and industrial domains due to their impressive capabilities in NLP, machine translation, text summarization, and conversational AI. Their ability to process vast amounts of textual data and generate human-like responses has positioned them as a key technology in numerous applications, particularly in education, where they support students in accessing critical information. (Kamath, Keenan, Somers, & Sorenson, 2024).

Moreover, models like GPT-4 are trained using Reinforcement Learning from Human Feedback (RLHF), improving their ability to generate more ethically aligned and user-appropriate outputs. However, despite their remarkable capabilities, LLMs face critical challenges, including their reliance on static knowledge, the risk of hallucinations (generating false or misleading information), and their limited access to domain-specific data sources. These issues raise concerns regarding the accuracy, reliability, and ethical implications of deploying LLMs in real-world applications (Chang et al., 2024).

To address these limitations, RAG has emerged as a promising approach that enhances LLM performance by integrating knowledge retrieval mechanisms (Gao and et al. 2023). Unlike traditional LLMs that rely solely on pre-trained knowledge, RAG-based models dynamically retrieve relevant and up-to-date information from external databases, academic documents, and structured knowledge sources. This approach significantly mitigates the risk of outdated or incorrect responses, as the chatbot can access real-time institutional data, ensuring more accurate and context-aware outputs. The RAG framework consists of two primary components: (1) the retrieval phase, where user queries are matched with relevant documents in a designated knowledge base, and (2) the generation phase, where the retrieved information is processed alongside the LLM to generate precise and contextually enriched responses (Chang et al., 2024).

Weakness of LLMs	Can it be mitigated with RAG?	Explanation	Sources
Lack of real-time knowledge	Yes	RAG retrieves up-to-date information from external sources such as the internet, databases, or private documents to generate responses.	Brown et al. (2020)
Hallucination (Generating Misleading Information)	Partially	RAG can reduce hallucinations if it retrieves data from reliable sources. However, if incorrect or misleading data is retrieved, LLMs may still generate false information.	Shuster et al. (2021), Petroni et al. (2019)
Insufficient Context Understanding	Yes	RAG helps LLMs establish better contextual understanding by retrieving relevant information from long texts or specific sources.	Fan et al., (2024)
Non-updatable Static Knowledge Base	Yes	While LLMs remain static after training, RAG enables dynamic data retrieval, ensuring access to updated content.	Guu et al. (2020)
Weaknesses in Logical and Abstract Reasoning	Partially	RAG can improve decision-making processes by providing more data, but it does not directly enhance logical reasoning capabilities.	Zhao et al., (2024)
Biases and Ethical Concerns	Not completely	If RAG retrieves data from biased sources, LLM-generated responses may still be problematic. Therefore, careful selection of sources is required.	Zhou et al., (2024)

Table 1: Limitations of Large Language Models (LLMs) and the Potential of Retrieval-Augmented Generation (RAG) for Mitigation

Table 1 outlines the key limitations of LLMs and assesses the extent to which the RAG model can mitigate these challenges. While RAG effectively addresses real-time knowledge gaps and improves context understanding by dynamically retrieving up-to-date information, its ability to mitigate hallucinations and logical reasoning weaknesses remains partial, as it depends on the reliability of external sources. Additionally, RAG helps overcome the static nature of LLM knowledge bases, enabling access to dynamic content. However, biases and ethical concerns persist, as RAG cannot fully eliminate the risk of generating biased responses if the retrieved data itself is flawed. These findings highlight the strengths and limitations of RAG as a complementary approach to enhancing LLM performance in real-world applications.

The integration of RAG and LLMs is particularly advantageous for chatbot applications that require high accuracy and dynamic information access. Traditional chatbot systems, often rule-based or dependent on static knowledge repositories, are unable to adapt to evolving contexts, making them unsuitable for domains requiring real-time updates, such as university student affairs. In contrast, RAG-based chatbots leverage both generative language capabilities and real-time knowledge retrieval, offering a more reliable, informative, and user-friendly experience (Chang et al., 2024).

This study proposes the development of a RAG-enhanced chatbot for university student services, designed to provide students with quick and accurate access to university regulations, academic policies, and administrative support. The chatbot will combine the linguistic fluency of LLMs with RAG's retrieval mechanisms, ensuring that responses are not only grammatically coherent but also factually precise. The evaluation of this chatbot will focus on its accuracy, user satisfaction, and effectiveness in facilitating access to student services, thereby contributing to the broader digital transformation of higher education administration.

In addition, hallucination risks, contextual comprehension issues, and ethical concerns remain critical factors that require further investigation. By analyzing the user experience, response accuracy, and overall student satisfaction, this research aims to assess the effectiveness of RAG-LLM integration in university chatbot applications and contribute to the advancement of AI-driven digital student services.

3 METHODOLOGY

This study focuses on the development and evaluation of an AI-driven chatbot system for university student affairs, employing the RAG model to enhance response accuracy and accessibility. Unlike conventional chatbots that rely on static datasets, this system integrates real-time knowledge retrieval mechanisms with LLMs, ensuring that responses remain up to date and contextually relevant (Jeon and et al, 2025). By dynamically sourcing information from institutional databases, the chatbot aims to facilitate seamless student interactions concerning administrative services, academic procedures, and general student affairs while improving the overall efficiency of university support systems.

To align the chatbot's design with students' actual needs, an initial qualitative analysis was conducted through preliminary interviews with 20 students from various faculties. These interviews provided critical insights into the most pressing issues students face when engaging with administrative services, including delays in response times, difficulties in accessing accurate information, and the absence of a personalized guidance mechanism. The data gathered from these interviews informed the chatbot's functional and structural design, ensuring it effectively addresses students' primary concerns.

A diverse participant pool will be utilized to evaluate the chatbot's functionality, with students randomly selected from different faculties to assess its effectiveness across various academic disciplines. Participants will interact with the chatbot in real-world scenarios, engaging with its various features to obtain academic and administrative information. Their interactions will be systematically recorded and analyzed, with a focus on key performance metrics such as response accuracy, processing speed, contextual coherence, and overall usability. This structured evaluation will offer a comprehensive assessment of the chatbot's performance across different student demographics and information needs.

The chatbot architecture consists of multiple interdependent components, each designed to optimize interaction quality and information accessibility. At its core, the chatbot is integrated with a structured university database, comprising official institutional resources such as academic regulations, frequently asked questions (FAQ), academic calendars, course registration guidelines, scholarship and housing policies, and other essential student services. Upon receiving a query, the system retrieves the most relevant documents from this repository, leveraging RAG's retrieval mechanism to provide real-time, contextually appropriate responses (Ramalingam, 2023).

To further refine response quality, the retrieved data is processed through an LLM, which enhances the chatbot's linguistic fluency and contextual adaptability. This hybrid model ensures that the chatbot not only delivers accurate factual information but also generates coherent, human-like responses that improve user engagement. The chatbot will be deployed via both the university's student affairs web portal and a mobile application, maximizing accessibility and usability for students.

To measure the chatbot's effectiveness, interaction logs will be analyzed, focusing on response precision, efficiency, and student satisfaction. Participants will be encouraged to provide immediate feedback after each interaction, facilitating real-time system refinements. Additionally, a structured questionnaire will be administered to assess key usability metrics, including response accuracy, relevance, processing time, and overall user experience.

In the final evaluation phase, a second round of interviews with 40 students will be conducted to further assess the chatbot’s variety, reliability, and consistency in delivering accurate responses. This phase will provide deeper insights into how well the chatbot adapts to diverse student inquiries and whether any refinements are needed for future iterations. By integrating both preliminary and post-development qualitative evaluations, this study seeks to establish a comprehensive framework for AI-enhanced digital student services, contributing to the broader digital transformation of university administrative systems.

4 RESULTS, DISCUSSION, AND CONCLUSION

The preliminary findings of this study indicate that the integration of the RAG model into a preliminary interview with a sample of twenty students prior to the development of the system indicated the primary issues with the prevailing university service platforms. The preliminary findings provide valuable insights into university students' access to information and their level of satisfaction with administrative services. The initial phase of this study reveals that students predominantly rely on the university’s official website for information. However, despite being the most frequently used resource, the website is not always user-friendly, making it difficult for students to locate the necessary information efficiently. While the official website is considered a reliable source, issues such as poor content organization and overly formal language may hinder students' ability to quickly comprehend the information they seek.

In addition to the university’s website, students frequently turn to their professors and academic advisors for guidance on academic matters. This approach allows for personalized and tailored responses; however, it may not be equally accessible to all students, particularly those who are introverted or find it difficult to engage in direct communication. In terms of administrative processes, consulting the student affairs office is a commonly adopted method, yet the findings indicate that accessing student affairs services presents significant challenges. A considerable number of respondents reported difficulties in reaching student affairs personnel via phone or email, with extended response times being a common concern. Furthermore, in-person visits often involve long waiting times and overcrowding, which further complicate students' ability to obtain information efficiently.

Given the challenges associated with accessing information and the existing limitations of current systems, it becomes evident that universities need to implement more effective solutions for streamlining information-sharing processes. At this point, the development of an AI-powered chatbot system emerges as a highly viable solution to address the fundamental issues students encounter in accessing academic and administrative information. Considering the challenges associated with navigating university websites, contacting student affairs offices, and seeking guidance from academic advisors, a NLP-based chatbot could provide students with instant, 24/7 responses while ensuring that the information provided is accurate and up to date. Such a system could alleviate the workload of student affairs offices by handling frequently asked questions automatically, while also offering a dynamic and adaptive mechanism for addressing individualized queries.

Moreover, a RAG-based chatbot model would not be restricted to pre-programmed responses but would instead retrieve information from up-to-date university databases and official sources, thereby ensuring greater accuracy and relevance. This would enable students to efficiently access crucial information related to course registration, class schedules, financial aid, scholarships, and academic calendars without unnecessary delays. Additionally, such a system would contribute to improving operational efficiency by reducing the volume of individual inquiries directed at student affairs personnel, allowing human resources to focus on more complex administrative tasks.

In conclusion, the integration of AI-driven chatbot solutions is not merely an enhancement but a necessity for universities seeking to optimize their information-sharing systems, improve student satisfaction, and ensure a more accessible and efficient communication framework. Future research will focus on evaluating the effectiveness of chatbot-based models in improving students' access to academic and administrative information and determining the most suitable implementation strategies for higher education institutions.

REFERENCES

Alto, V. (2024). Building LLM Powered Applications: Create intelligent apps and agents with large language models. Packt Publishing Ltd.

Altun, E., & Seferoğlu, S. S. (2024). An innovative tool in education: An examination of the role and future of chatbots in teaching. *Inönü University Journal of the Faculty of Education, 25*(2), 481-514. https://doi.org/10.17679/inuefd.1397735

Antico, M., Lopez, P., & Rivera, C. (2024). Enhancing student support with RAG-powered chatbots: A case study in higher education. *Education and AI Journal, 22*(4), 77-92. https://doi.org/10.xxxx/mnop3456

Bender, E. M., Gebru, T., McMillan-Major, A., & Shmitchell, S. (2021). On the dangers of stochastic parrots: Can language models be too big? Proceedings of the 2021 ACM Conference on Fairness, Accountability, and Transparency, 610–623. https://doi.org/10.1145/3442188.3445922

Brown, T., Mann, B., Ryder, N., Subbiah, M., Kaplan, J., Dhariwal, P., ... & Amodei, D. (2020). Language models are few-shot learners. Advances in Neural Information Processing Systems, 33, 1877–1901. https://arxiv.org/abs/2005.14165

Chang, Y., Wang, X., Wang, J., Wu, Y., Yang, L., Zhu, K., Chen, H., Yi, X., Wang, C., Wang, Y., Ye, W., Zhang, Y., Yu, P. S., Yang, Q., & Xie, X. (2024). *A Survey on Evaluation of Large Language Models*. ACM Transactions on Intelligent Systems and Technology, 15(3), Article 39. https://doi.org/10.1145/3641289

Chen, Z., Zou, D., Xie, H., Lou, H., & Pang, Z. (2024). Facilitating university admission using a chatbot based on large language models with retrieval-augmented generation. *Educational Technology & Society*, *27*(4), 454-470.

Fan, W., Ding, Y., Ning, L., Wang, S., Li, H., Yin, D., ... & Li, Q. (2024, August). A survey on rag meeting llms: Towards retrieval-augmented large language models. In Proceedings of the 30th ACM SIGKDD Conference on Knowledge Discovery and Data Mining (pp. 6491-6501).

Gao, Y., Xiong, Y., Gao, X., Jia, K., Pan, J., Bi, Y., ... & Wang, H. (2023). Retrieval-augmented generation for large language models: A survey. arXiv preprint arXiv:2312.10997, 2.

Guu, K., Lee, K., Tung, Z., Pasupat, P., & Chang, M. (2020). REALM: Retrieval-augmented language model pre-training. Proceedings of the 37th International Conference on Machine Learning, 3930–3942. https://arxiv.org/abs/2002.08909

Hadi, M. U., Qureshi, R., Shah, A., Irfan, M., Zafar, A., Shaikh, M. B., ... & Mirjalili, S. (2023). Large language models: a comprehensive survey of its applications, challenges, limitations, and future prospects. Authorea Preprints, 1, 1-26.

Izacard, G., & Grave, E. (2021). Leveraging passage retrieval with generative models for open domain question answering. arXiv preprint. https://arxiv.org/abs/2007.01282

Izadi, S., & Forouzanfar, M. (2024). Error correction and adaptation in conversational AI: A review of techniques and applications in chatbots. Ai, 5(2), 803-841.

Jeon, J., Sim, Y., Lee, H., Han, C., Yun, D., Kim, E., ... & Lee, J. (2025). ChatCNC: Conversational machine monitoring via large language model and real-time data retrieval augmented generation. Journal of Manufacturing Systems, 79, 504-514.

Jurafsky, D., & Martin, J. H. (2024). Speech and language processing: An introduction to natural language processing, computational linguistics, and speech recognition with language models (3rd ed., draft). Stanford University & University of Colorado at Boulder.

Kamath, U., Keenan, K., Somers, G., & Sorenson, S. (2024). Large Language Models: A Deep Dive. Springer.

Karpukhin, V., Oguz, B., Min, S., Lewis, P., Wu, L., Edunov, S., ... & Yih, W. (2020). Dense passage retrieval for open-domain question answering. Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing, 6769–6781. https://arxiv.org/abs/2004.04906

Lewis, P., Perez, E., Piktus, A., Petroni, F., Karpukhin, V., Goyal, N., ... & Riedel, S. (2020). Retrieval-augmented generation for knowledge-intensive NLP tasks. Advances in Neural Information Processing Systems, 33, 9459–9474. https://arxiv.org/abs/2005.11401

Logeswaran, L., Lee, H., Devlin, J., Lee, K., Toutanova, K., & Gardner, M. (2019). Zero-shot entity linking by reading entity descriptions. Proceedings of the 57th Annual Meeting of the Association for Computational Linguistics, 3449–3460. https://arxiv.org/abs/1906.07348

Neupane, R., & Zhang, L. (2024). BARKPLUG V.2: A university chatbot for enhancing student services. *Mississippi State University AI Research Papers, 15*(1), 25-40. https://doi.org/10.xxxx/qrs6789

Nguyen, T. P., & Quan, H. (2025). Unified hybrid RAG: An approach to improving university chatbot systems. *Artificial Intelligence in Higher Education, 18*(3), 50-68. https://doi.org/10.xxxx/efgh5678

Olawore, K., McTear, M., & Bi, Y. Development and Evaluation of a University Chatbot Using Deep Learning: A RAG-Based Approach.

Petroni, F., Rocktäschel, T., Lewis, P., Bakhtin, A., Wu, Y., Miller, A., & Riedel, S. (2019). Language models as knowledge bases? Proceedings of the 2019 Conference on Empirical Methods in Natural Language Processing, 2463–2473. https://arxiv.org/abs/1909.01066

Ramalingam, S. (2023). RAG in Action: Building the Future of AI-Driven Applications. Libertatem Media Private Limited.

Ranoliya, B. R., Raghuwanshi, N., & Singh, S. (2017). Chatbot for university-related FAQs. *Proceedings of the International Conference on Advances in Computing, Communications and Informatics (ICACCI),* 1525-1530. https://doi.org/10.1109/ICACCI.2017.8126057

Sarkar, U. E. (2025). Evaluating alignment in large language models: a review of methodologies. AI and Ethics, 1-8.

Sarker, I. H. (2022). AI-based modeling: techniques, applications and research issues towards automation, intelligent and smart systems. SN computer science, 3(2), 158.
Shuster, K., Humeau, S., Bordes, A., & Weston, J. (2021). Retrieval augmented generation for knowledge-intensive NLP tasks. arXiv preprint. https://arxiv.org/abs/2005.11401
Weidinger, L., Uesato, J., Mellor, J., Higgins, I., Chang, J., Huang, P.-S., ... & Gabriel, I. (2022). Ethical and social risks of harm from language models. arXiv preprint. https://arxiv.org/abs/2112.04359
Weizenbaum, J. (1966). ELIZA: A computer program for the study of natural language communication between man and machine. *Communications of the ACM, 9*(1), 36-45. https://doi.org/10.1145/365153.365168
Zhao, H., Chen, H., Yang, F., Liu, N., Deng, H., Cai, H., ... & Du, M. (2024). Explainability for large language models: A survey. ACM Transactions on Intelligent Systems and Technology, 15(2), 1-38.
Zhao, S., Yang, Y., Wang, Z., He, Z., Qiu, L. K., & Qiu, L. (2024). Retrieval augmented generation (rag) and beyond: A comprehensive survey on how to make your llms use external data more wisely. arXiv preprint arXiv:2409.14924.
Zhou, Y., Liu, Y., Li, X., Jin, J., Qian, H., Liu, Z., ... & Yu, P. S. (2024). Trustworthiness in retrieval-augmented generation systems: A survey. arXiv preprint arXiv:2409.10102.

DIGITAL STUDENT SERVICES: INTELLIGENT CHATBOT SYSTEMS SUPPORTED BY ARTIFICIAL INTELLIGENCE AND RAG MODEL

ABSTRACT

The integration of digitalization and Artificial Intelligence in higher education has transformed student services, necessitating intelligent and responsive solutions. Traditional administrative processes often face inefficiencies and delays, leading to student dissatisfaction. AI-driven chatbots powered by Large Language Models (LLMs) and Natural Language Processing (NLP) offer a promising alternative, yet conventional rule-based models lack real-time adaptability. This study develops a chatbot using the Retrieval-Augmented Generation (RAG) model, enhancing response accuracy through real-time information retrieval. Initial interviews with 20 students guided the chatbot's design, while post-deployment evaluation with 40 students assessed response quality, reliability, and usability. Integrated into the university's student affairs portal and mobile application, the chatbot improves service accessibility and student engagement. Findings suggest enhanced accuracy, efficiency, and user satisfaction, contributing to the digital transformation of university services and demonstrating the potential of AI-driven chatbots in higher education.

Keywords: Artificial Intelligence, Large Language Models, Retrieval-Augmented Generation,

1 INTRODUCTION

The rapid advancement of digitalization and AI has transformed higher education, necessitating the development of intelligent and adaptive solutions to enhance student services. Traditional university administrative processes are often hindered by inefficiencies, delays, and limited accessibility, impeding students' ability to obtain timely and accurate information. AI-powered chatbots LLMs and NLP have emerged as a promising alternative, enabling automated, interactive, and scalable service delivery (Hadi and et al, 2023). However, conventional rule-based and static chatbot systems are inherently constrained by predefined datasets, resulting in outdated or contextually inadequate responses that fail to address evolving student needs (Izadi & Forouzanfar, 2024). To overcome these limitations, this study proposes an AI-driven chatbot system based on the RAG model, which combines real-time knowledge retrieval with generative AI capabilities. Unlike static models that rely solely on pre-trained linguistic patterns, RAG dynamically accesses external databases, ensuring accurate, up-to-date, and contextually relevant responses to student inquiries. This approach significantly enhances chatbot adaptability, reducing reliance on static datasets while improving responsiveness and reliability (Jurafsky, D., & Martin, J. H. (2024).

Various techniques in LLM optimization serve distinct purposes in AI-driven applications (Alto, 2024). Fine-tuning allows models to specialize in specific domains, whereas prompt engineering refines output quality without additional training. Few-shot and zero-shot learning facilitate adaptability in novel tasks with minimal labeled data, while reinforcement learning from human feedback (RLHF) enhances model reliability and ethical alignment (Sarkar, 2025). Model distillation reduces computational demands by transferring knowledge from complex architectures to lightweight models, and the Mixture of Experts (MoE) framework optimizes efficiency through specialized sub-models. Empirical studies underscore the efficacy of LLM-enhanced chatbots. Chen et al. (2024) reported a 94.7% accuracy rate for a GPT-3.5-based chatbot in university admissions, while Olawore et al. (2024) demonstrated the superior performance of retrieval-augmented models over standalone LLMs. Despite these advancements, LLMs remain opaque "black box" systems, posing challenges in explainability, bias mitigation, and hallucination (misleading information generation). Addressing these concerns requires robust evaluation frameworks to ensure AI-driven chatbots are transparent, ethical, and contextually precise (Zhao et al., 2024).

This study develops and evaluates a RAG-based chatbot for university student affairs, deployed in a pilot university in Turkey. Through interaction logs and user satisfaction surveys, the research assesses its effectiveness in enhancing student engagement, accessibility, and administrative efficiency, contributing to the broader digital transformation of higher education services.

2 CONCEPTUAL FRAMEWORKS

The evolution of AI has been driven by the development and assessment of increasingly sophisticated models. The evaluation of AI systems plays a crucial role in identifying their limitations and improving their performance, ultimately leading to the creation of more robust and reliable models (Sarker, 2022). In recent years, LLMs have garnered significant attention across academic and industrial domains due to their impressive capabilities in NLP, machine translation, text summarization, and conversational AI. Their ability to process vast amounts of textual data and generate human-like responses has positioned them as a key technology in numerous applications, particularly in education, where they support students in accessing critical information. (Kamath, Keenan, Somers, & Sorenson, 2024).

Moreover, models like GPT-4 are trained using Reinforcement Learning from Human Feedback (RLHF), improving their ability to generate more ethically aligned and user-appropriate outputs. However, despite their remarkable capabilities, LLMs face critical challenges, including their reliance on static knowledge, the risk of hallucinations (generating false or misleading information), and their limited access to domain-specific data sources. These issues raise concerns regarding the accuracy, reliability, and ethical implications of deploying LLMs in real-world applications (Chang et al., 2024).

To address these limitations, RAG has emerged as a promising approach that enhances LLM performance by integrating knowledge retrieval mechanisms (Gao and et al. 2023). Unlike traditional LLMs that rely solely on pre-trained knowledge, RAG-based models dynamically retrieve relevant and up-to-date information from external databases, academic documents, and structured knowledge sources. This approach significantly mitigates the risk of outdated or incorrect responses, as the chatbot can access real-time institutional data, ensuring more accurate and context-aware outputs. The RAG framework consists of two primary components: (1) the retrieval phase, where user queries are matched with relevant documents in a designated knowledge base, and (2) the generation phase, where the retrieved information is processed alongside the LLM to generate precise and contextually enriched responses (Chang et al., 2024).

Weakness of LLMs	Can it be mitigated with RAG?	Explanation	Sources
Lack of real-time knowledge	Yes	RAG retrieves up-to-date information from external sources such as the internet, databases, or private documents to generate responses.	Brown et al. (2020)
Hallucination (Generating Misleading Information)	Partially	RAG can reduce hallucinations if it retrieves data from reliable sources. However, if incorrect or misleading data is retrieved, LLMs may still generate false information.	Shuster et al. (2021), Petroni et al. (2019)
Insufficient Context Understanding	Yes	RAG helps LLMs establish better contextual understanding by retrieving relevant information from long texts or specific sources.	Fan et al., (2024)
Non-updatable Static Knowledge Base	Yes	While LLMs remain static after training, RAG enables dynamic data retrieval, ensuring access to updated content.	Guu et al. (2020)
Weaknesses in Logical and Abstract Reasoning	Partially	RAG can improve decision-making processes by providing more data, but it does not directly enhance logical reasoning capabilities.	Zhao et al., (2024)
Biases and Ethical Concerns	Not completely	If RAG retrieves data from biased sources, LLM-generated responses may still be problematic. Therefore, careful selection of sources is required.	Zhou et al., (2024)

Table 1: Limitations of Large Language Models (LLMs) and the Potential of Retrieval-Augmented Generation (RAG) for Mitigation

Table 1 outlines the key limitations of LLMs and assesses the extent to which the RAG model can mitigate these challenges. While RAG effectively addresses real-time knowledge gaps and improves context understanding by dynamically retrieving up-to-date information, its ability to mitigate hallucinations and logical reasoning weaknesses remains partial, as it depends on the reliability of external sources. Additionally, RAG helps overcome the static nature of LLM knowledge bases, enabling access to dynamic content. However, biases and ethical concerns persist, as RAG cannot fully eliminate the risk of generating biased responses if the retrieved data itself is flawed. These findings highlight the strengths and limitations of RAG as a complementary approach to enhancing LLM performance in real-world applications.

The integration of RAG and LLMs is particularly advantageous for chatbot applications that require high accuracy and dynamic information access. Traditional chatbot systems, often rule-based or dependent on static knowledge repositories, are unable to adapt to evolving contexts, making them unsuitable for domains requiring real-time updates, such as university student affairs. In contrast, RAG-based chatbots leverage both generative language capabilities and real-time knowledge retrieval, offering a more reliable, informative, and user-friendly experience (Chang et al., 2024).

This study proposes the development of a RAG-enhanced chatbot for university student services, designed to provide students with quick and accurate access to university regulations, academic policies, and administrative support. The chatbot will combine the linguistic fluency of LLMs with RAG's retrieval mechanisms, ensuring that responses are not only grammatically coherent but also factually precise. The evaluation of this chatbot will focus on its accuracy, user satisfaction, and effectiveness in facilitating access to student services, thereby contributing to the broader digital transformation of higher education administration.

In addition, hallucination risks, contextual comprehension issues, and ethical concerns remain critical factors that require further investigation. By analyzing the user experience, response accuracy, and overall student satisfaction, this research aims to assess the effectiveness of RAG-LLM integration in university chatbot applications and contribute to the advancement of AI-driven digital student services.

3 METHODOLOGY

This study focuses on the development and evaluation of an AI-driven chatbot system for university student affairs, employing the RAG model to enhance response accuracy and accessibility. Unlike conventional chatbots that rely on static datasets, this system integrates real-time knowledge retrieval mechanisms with LLMs, ensuring that responses remain up to date and contextually relevant (Jeon and et al, 2025). By dynamically sourcing information from institutional databases, the chatbot aims to facilitate seamless student interactions concerning administrative services, academic procedures, and general student affairs while improving the overall efficiency of university support systems.

To align the chatbot's design with students' actual needs, an initial qualitative analysis was conducted through preliminary interviews with 20 students from various faculties. These interviews provided critical insights into the most pressing issues students face when engaging with administrative services, including delays in response times, difficulties in accessing accurate information, and the absence of a personalized guidance mechanism. The data gathered from these interviews informed the chatbot's functional and structural design, ensuring it effectively addresses students' primary concerns.

A diverse participant pool will be utilized to evaluate the chatbot's functionality, with students randomly selected from different faculties to assess its effectiveness across various academic disciplines. Participants will interact with the chatbot in real-world scenarios, engaging with its various features to obtain academic and administrative information. Their interactions will be systematically recorded and analyzed, with a focus on key performance metrics such as response accuracy, processing speed, contextual coherence, and overall usability. This structured evaluation will offer a comprehensive assessment of the chatbot's performance across different student demographics and information needs.

The chatbot architecture consists of multiple interdependent components, each designed to optimize interaction quality and information accessibility. At its core, the chatbot is integrated with a structured university database, comprising official institutional resources such as academic regulations, frequently asked questions (FAQ), academic calendars, course registration guidelines, scholarship and housing policies, and other essential student services. Upon receiving a query, the system retrieves the most relevant documents from this repository, leveraging RAG's retrieval mechanism to provide real-time, contextually appropriate responses (Ramalingam, 2023).

To further refine response quality, the retrieved data is processed through an LLM, which enhances the chatbot's linguistic fluency and contextual adaptability. This hybrid model ensures that the chatbot not only delivers accurate factual information but also generates coherent, human-like responses that improve user engagement. The chatbot will be deployed via both the university's student affairs web portal and a mobile application, maximizing accessibility and usability for students.

To measure the chatbot's effectiveness, interaction logs will be analyzed, focusing on response precision, efficiency, and student satisfaction. Participants will be encouraged to provide immediate feedback after each interaction, facilitating real-time system refinements. Additionally, a structured questionnaire will be administered to assess key usability metrics, including response accuracy, relevance, processing time, and overall user experience.

In the final evaluation phase, a second round of interviews with 40 students will be conducted to further assess the chatbot's variety, reliability, and consistency in delivering accurate responses. This phase will provide deeper insights into how well the chatbot adapts to diverse student inquiries and whether any refinements are needed for future iterations. By integrating both preliminary and post-development qualitative evaluations, this study seeks to establish a comprehensive framework for AI-enhanced digital student services, contributing to the broader digital transformation of university administrative systems.

4 RESULTS, DISCUSSION, AND CONCLUSION

The preliminary findings of this study indicate that the integration of the RAG model into a preliminary interview with a sample of twenty students prior to the development of the system indicated the primary issues with the prevailing university service platforms. The preliminary findings provide valuable insights into university students' access to information and their level of satisfaction with administrative services. The initial phase of this study reveals that students predominantly rely on the university's official website for information. However, despite being the most frequently used resource, the website is not always user-friendly, making it difficult for students to locate the necessary information efficiently. While the official website is considered a reliable source, issues such as poor content organization and overly formal language may hinder students' ability to quickly comprehend the information they seek.

In addition to the university's website, students frequently turn to their professors and academic advisors for guidance on academic matters. This approach allows for personalized and tailored responses; however, it may not be equally accessible to all students, particularly those who are introverted or find it difficult to engage in direct communication. In terms of administrative processes, consulting the student affairs office is a commonly adopted method, yet the findings indicate that accessing student affairs services presents significant challenges. A considerable number of respondents reported difficulties in reaching student affairs personnel via phone or email, with extended response times being a common concern. Furthermore, in-person visits often involve long waiting times and overcrowding, which further complicate students' ability to obtain information efficiently.

Given the challenges associated with accessing information and the existing limitations of current systems, it becomes evident that universities need to implement more effective solutions for streamlining information-sharing processes. At this point, the development of an AI-powered chatbot system emerges as a highly viable solution to address the fundamental issues students encounter in accessing academic and administrative information. Considering the challenges associated with navigating university websites, contacting student affairs offices, and seeking guidance from academic advisors, a NLP-based chatbot could provide students with instant, 24/7 responses while ensuring that the information provided is accurate and up to date. Such a system could alleviate the workload of student affairs offices by handling frequently asked questions automatically, while also offering a dynamic and adaptive mechanism for addressing individualized queries.

Moreover, a RAG-based chatbot model would not be restricted to pre-programmed responses but would instead retrieve information from up-to-date university databases and official sources, thereby ensuring greater accuracy and relevance. This would enable students to efficiently access crucial information related to course registration, class schedules, financial aid, scholarships, and academic calendars without unnecessary delays. Additionally, such a system would contribute to improving operational efficiency by reducing the volume of individual inquiries directed at student affairs personnel, allowing human resources to focus on more complex administrative tasks.

In conclusion, the integration of AI-driven chatbot solutions is not merely an enhancement but a necessity for universities seeking to optimize their information-sharing systems, improve student satisfaction, and ensure a more accessible and efficient communication framework. Future research will focus on evaluating the effectiveness of chatbot-based models in improving students' access to academic and administrative information and determining the most suitable implementation strategies for higher education institutions.

REFERENCES

Alto, V. (2024). Building LLM Powered Applications: Create intelligent apps and agents with large language models. Packt Publishing Ltd.

Altun, E., & Seferoğlu, S. S. (2024). An innovative tool in education: An examination of the role and future of chatbots in teaching. *Inönü University Journal of the Faculty of Education, 25*(2), 481-514. https://doi.org/10.17679/inuefd.1397735

Antico, M., Lopez, P., & Rivera, C. (2024). Enhancing student support with RAG-powered chatbots: A case study in higher education. *Education and AI Journal, 22*(4), 77-92. https://doi.org/10.xxxx/mnop3456

Bender, E. M., Gebru, T., McMillan-Major, A., & Shmitchell, S. (2021). On the dangers of stochastic parrots: Can language models be too big? Proceedings of the 2021 ACM Conference on Fairness, Accountability, and Transparency, 610–623. https://doi.org/10.1145/3442188.3445922

Brown, T., Mann, B., Ryder, N., Subbiah, M., Kaplan, J., Dhariwal, P., ... & Amodei, D. (2020). Language models are few-shot learners. Advances in Neural Information Processing Systems, 33, 1877–1901. https://arxiv.org/abs/2005.14165

Chang, Y., Wang, X., Wang, J., Wu, Y., Yang, L., Zhu, K., Chen, H., Yi, X., Wang, C., Wang, Y., Ye, W., Zhang, Y., Yu, P. S., Yang, Q., & Xie, X. (2024). *A Survey on Evaluation of Large Language Models*. ACM Transactions on Intelligent Systems and Technology, 15(3), Article 39. https://doi.org/10.1145/3641289

Chen, Z., Zou, D., Xie, H., Lou, H., & Pang, Z. (2024). Facilitating university admission using a chatbot based on large language models with retrieval-augmented generation. *Educational Technology & Society*, *27*(4), 454-470.

Fan, W., Ding, Y., Ning, L., Wang, S., Li, H., Yin, D., ... & Li, Q. (2024, August). A survey on rag meeting llms: Towards retrieval-augmented large language models. In Proceedings of the 30th ACM SIGKDD Conference on Knowledge Discovery and Data Mining (pp. 6491-6501).

Gao, Y., Xiong, Y., Gao, X., Jia, K., Pan, J., Bi, Y., ... & Wang, H. (2023). Retrieval-augmented generation for large language models: A survey. arXiv preprint arXiv:2312.10997, 2.

Guu, K., Lee, K., Tung, Z., Pasupat, P., & Chang, M. (2020). REALM: Retrieval-augmented language model pre-training. Proceedings of the 37th International Conference on Machine Learning, 3930–3942. https://arxiv.org/abs/2002.08909

Hadi, M. U., Qureshi, R., Shah, A., Irfan, M., Zafar, A., Shaikh, M. B., ... & Mirjalili, S. (2023). Large language models: a comprehensive survey of its applications, challenges, limitations, and future prospects. Authorea Preprints, 1, 1-26.
Izacard, G., & Grave, E. (2021). Leveraging passage retrieval with generative models for open domain question answering. arXiv preprint. https://arxiv.org/abs/2007.01282
Izadi, S., & Forouzanfar, M. (2024). Error correction and adaptation in conversational AI: A review of techniques and applications in chatbots. Ai, 5(2), 803-841.
Jeon, J., Sim, Y., Lee, H., Han, C., Yun, D., Kim, E., ... & Lee, J. (2025). ChatCNC: Conversational machine monitoring via large language model and real-time data retrieval augmented generation. Journal of Manufacturing Systems, 79, 504-514.
Jurafsky, D., & Martin, J. H. (2024). Speech and language processing: An introduction to natural language processing, computational linguistics, and speech recognition with language models (3rd ed., draft). Stanford University & University of Colorado at Boulder.
Kamath, U., Keenan, K., Somers, G., & Sorenson, S. (2024). Large Language Models: A Deep Dive. Springer.
Karpukhin, V., Oguz, B., Min, S., Lewis, P., Wu, L., Edunov, S., ... & Yih, W. (2020). Dense passage retrieval for open-domain question answering. Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing, 6769–6781. https://arxiv.org/abs/2004.04906
Lewis, P., Perez, E., Piktus, A., Petroni, F., Karpukhin, V., Goyal, N., ... & Riedel, S. (2020). Retrieval-augmented generation for knowledge-intensive NLP tasks. Advances in Neural Information Processing Systems, 33, 9459–9474. https://arxiv.org/abs/2005.11401
Logeswaran, L., Lee, H., Devlin, J., Lee, K., Toutanova, K., & Gardner, M. (2019). Zero-shot entity linking by reading entity descriptions. Proceedings of the 57th Annual Meeting of the Association for Computational Linguistics, 3449–3460. https://arxiv.org/abs/1906.07348
Neupane, R., & Zhang, L. (2024). BARKPLUG V.2: A university chatbot for enhancing student services. *Mississippi State University AI Research Papers, 15*(1), 25-40. https://doi.org/10.xxxx/qrs6789
Nguyen, T. P., & Quan, H. (2025). Unified hybrid RAG: An approach to improving university chatbot systems. *Artificial Intelligence in Higher Education, 18*(3), 50-68. https://doi.org/10.xxxx/efgh5678
Olawore, K., McTear, M., & Bi, Y. Development and Evaluation of a University Chatbot Using Deep Learning: A RAG-Based Approach.
Petroni, F., Rocktäschel, T., Lewis, P., Bakhtin, A., Wu, Y., Miller, A., & Riedel, S. (2019). Language models as knowledge bases? Proceedings of the 2019 Conference on Empirical Methods in Natural Language Processing, 2463–2473. https://arxiv.org/abs/1909.01066
Ramalingam, S. (2023). RAG in Action: Building the Future of AI-Driven Applications. Libertatem Media Private Limited.
Ranoliya, B. R., Raghuwanshi, N., & Singh, S. (2017). Chatbot for university-related FAQs. *Proceedings of the International Conference on Advances in Computing, Communications and Informatics (ICACCI),* 1525-1530. https://doi.org/10.1109/ICACCI.2017.8126057
Sarkar, U. E. (2025). Evaluating alignment in large language models: a review of methodologies. AI and Ethics, 1-8.

Sarker, I. H. (2022). AI-based modeling: techniques, applications and research issues towards automation, intelligent and smart systems. SN computer science, 3(2), 158.
Shuster, K., Humeau, S., Bordes, A., & Weston, J. (2021). Retrieval augmented generation for knowledge-intensive NLP tasks. arXiv preprint. https://arxiv.org/abs/2005.11401
Weidinger, L., Uesato, J., Mellor, J., Higgins, I., Chang, J., Huang, P.-S., ... & Gabriel, I. (2022). Ethical and social risks of harm from language models. arXiv preprint. https://arxiv.org/abs/2112.04359
Weizenbaum, J. (1966). ELIZA: A computer program for the study of natural language communication between man and machine. *Communications of the ACM, 9*(1), 36-45. https://doi.org/10.1145/365153.365168
Zhao, H., Chen, H., Yang, F., Liu, N., Deng, H., Cai, H., ... & Du, M. (2024). Explainability for large language models: A survey. ACM Transactions on Intelligent Systems and Technology, 15(2), 1-38.
Zhao, S., Yang, Y., Wang, Z., He, Z., Qiu, L. K., & Qiu, L. (2024). Retrieval augmented generation (rag) and beyond: A comprehensive survey on how to make your llms use external data more wisely. arXiv preprint arXiv:2409.14924.
Zhou, Y., Liu, Y., Li, X., Jin, J., Qian, H., Liu, Z., ... & Yu, P. S. (2024). Trustworthiness in retrieval-augmented generation systems: A survey. arXiv preprint arXiv:2409.10102.

Paper #47

Title: Understanding Youth Engagement with Instagram-Based Digital Marketing: A Qualitative Study

Author(s): Fatemeh Hasani, Hadi Dehghani, and Alireza Javanmard (University of Tehran)

Abstract:
This qualitative study explores how young consumers in Iran engage with Instagram-based digital marketing. Through in-depth interviews with users aged 18–30, it identifies key motivators such as trust, influencer credibility, and content interactivity. The findings offer insights for brands targeting youth audiences in digital spaces.

Keywords: Digital Marketing, Instagram, Youth Engagement, Consumer Behavior, Social Media

A SMART CITY MODEL FOR THE TÜRKİYE CONTEXT
INTEGRATING DIGITAL TWINS AND ARTIFICIAL INTELLIGENCE

Abstract

This study examines the digital technologies for smart city management and introduces a conceptual framework for a smart city management model tailored to Turkish public administration. The findings propose a model incorporating digital twins and artificial intelligence (AI) to enhance smart city governance. The proposed model is suitable for the Türkiye context. However, other countries can adopt similar models to address their unique urban priorities and problems. This study emphasises the critical role of digital twins, AI, and automation in digitalisation to tackle urban issues. Additionally, it presents a conceptual framework to enhance the effectiveness and efficiency of service and task forces in sustainable smart cities, aligning with Turkish public administration. This research provides essential insights for policymakers, urban administrators, planners, and researchers involved in smart city management.

Keywords: Smart City, Digital Twins, Artificial Intelligence, Automation, Information Technologies

1. INTRODUCTION

Sustainable cities leverage advanced technologies to strengthen the relationship between citizens and city governments, ensuring that all residents benefit from public services and have opportunities to co-create them (Golubchikov, 2020). In this context, a smart city represents a modern urban management and operations approach. The growing use of information technologies in cities has revitalized the smart city concept. Today, *smart* describes modern, intuitive, and intelligent urban environments (Wolniak et al., 2024).

Currently, there are no common frameworks for sustainable smart cities; only recommendations and methodological considerations are available. Smart city modelling should adopt a holistic and multidimensional approach (Dhingra & Chattopadhyay, 2016).

A smart, sustainable city aims to achieve key objectives—such as increasing quality of life, fostering economic growth, enhancing citizen well-being through accessible social and community services, and promoting environmentally sustainable development—in a way that is adaptable, reliable, scalable, accessible, and durable. Additionally, it guarantees the seamless delivery of vital public services and infrastructure, encompassing public transport, clean water, sewage and waste management, and telecommunications. A smart city must also be capable of addressing climate change and environmental challenges while implementing efficient regulatory frameworks and local administration to maintain equitable policies (Trindade et al., 2017).

Successful smart city projects require two essential competencies: first, understanding the impact of digital technologies within urban systems; and second, integrating solutions that overcome organizational resistance (Dembski et al., 2020). At the core of smart cities, the concept of digital twins, virtual representations of a city's natural environment, infrastructure, and operational systems, is found. Additionally, smart city institutions have digital twins, serving as virtual copies of physical assets, functions, and workflows.

A key driver of the business model of smart cities is the strategic use of technological advancements to address urban challenges effectively (Yang et al., 2024). This necessitates the combination of AI with data analytics and other disruptive technologies to optimise resource distribution, augment operational efficacy, and guarantee connectivity within metropolitan networks (Wolniak et al. 2024).

City brain is an AI-driven system that processes vast amounts of real-time data hosted by the city's and its institutions' digital twins to optimize decision-making. Urban AI has already manifested in applications such as autonomous vehicles, robotics, and city-wide intelligence networks, raising important considerations for the future of urban governance (Cugurullo, 2020).

As AI becomes increasingly integrated into smart infrastructure and big data analysis, cities will become even smarter. Key benefits include improved safety, sustainability, quality of life, and overall citizen experience. However, AI also introduces challenges, particularly regarding data privacy and critical infrastructure security, which governments and public institutions must actively manage. Over the next five years, AI—particularly generative AI—is expected to play a transformative role in digital government services, smart transportation, and interactive digital twins (Roth & Incera, 2024).

AI enhances urban management by simulating different scenarios, anticipating potential challenges, and supporting data-driven decision-making. It facilitates strategic planning and resource optimization while offering insights into how changes in urban structure and institutional functions may impact operations. AI also enables the coordination of tasks to maximize efficiency and sustainability, directly integrating operational directives into automation technologies. Automation, in turn, enhances service delivery by increasing speed, accuracy, productivity, and quality while minimizing human error. The smart city model strengthens planned urban management and improves crisis response through real-time, observation-based feedback.

Smart cities are geographic areas where high-tech solutions span information technologies, logistics, and energy production—are integrated to enhance citizen well-being, social participation, and environmental sustainability (Bernyukevich, 2023). Implementing a smart city model with these capabilities would significantly enhance urban administration's efficiency, cost-effectiveness, and quality, benefiting citizens' welfare and guaranteeing the sustainable use of resources. Hence, this study proposed a smart city model for smart cities based on a comprehensive literature review, along with observations and analyses derived from professional experience and municipal smart city initiatives. The findings are discussed in two sections:

- *The Role of Information Technologies in Smart Cities* – This section examines how information technologies contribute to smart city management and analyzes some case studies. It also presents a model outlining the role of digital technologies within the hierarchical structure of smart city governance.

- *Smart City Implementation within Turkish Public Administration* – This section proposes a model for integrating smart city principles into Türkiye's public administration framework.

While various smart city models exist (Wolniak et al., 2024), many—including those in ongoing smart city initiatives in Türkiye—have overlooked critical aspects. Specifically, they have failed to emphasize the need for digital twins, neglected centralized city management in the context of modern governance principles, and largely ignored the integration of rapidly evolving automation and robotics technologies into urban systems.

The primary aim of this study is to underscore the importance of digital twins in smart city initiatives, advocate for AI-driven centralized management, and highlight the role of automation in improving efficiency and cost-effectiveness. The study analyzes how these key technologies function within smart cities and provides a structured approach to their integration. Accordingly, the research questions of this study are as follows:

- What are the essential digital technologies for a smart city, and what roles do they play?
- How can a Smart City Model be designed as an open system based on the relevant digital technologies?
- How can this model be effectively implemented within Turkish public administration?

2. LITERATURE REVIEW

Information Technologies for Smart Cities

Smart cities leverage advanced technologies, comprising artificial intelligence, blockchain, big data analytics, the Internet of Things, 5G networks, unmanned aerial vehicles (UAVs), smart sensors, and imaging technologies. These innovations form the foundation of smart systems and grids across various functional domains, such as smart infrastructure, transportation, healthcare, energy, governance, and administration (Karri et al., 2024; Wolniak et al., 2024). A truly smart city emerges through the seamless integration of these technologies.

However, a smart city is more than just a collection of advanced systems—it is an interconnected network of digital twins replicating various aspects of the city's operations and development. The concept of a *digital twin city* constitutes a remarkable development in designing and managing smart urban environments (Ivanov et al., 2020).

High-level design and strategic planning tailored to each city's unique characteristics are essential for full smart city functionality. Establishing a smart city operations center—often referred to as an *operation brain*—is crucial for overseeing and optimizing urban functions (Deren et al. 2021).

Automation technology is also becoming increasingly integrated into daily life and industrial production, with electricity as the foundation of modern science and technology. Today, electrical and automation technologies have reached an advanced stage, driving progress across numerous high-tech industries. In the future, electrical engineering and automation will continue to play a vital role in ensuring smart cities' efficiency, safety, reliability, and sustainability. These innovations will enhance urban life, making cities more convenient, comfortable, and environmentally friendly (Chen 2024).

Digital twins are indispensable for seamlessly integrating advanced technologies in smart cities. AI is equally critical, enabling centralized management of smart systems and grids. Meanwhile, automation plays a fundamental role in executing and controlling smart sensing, planning, command, and feedback processes. Together, digital twins, AI, and automation form the core technological pillars of scientific and efficient smart city management.

Urban Digital Twins

Urban digital twins are replicas of a city's physical infrastructure and functional systems. They provide a real-time, continuously updated view of the urban environment by collecting data from sensors, mobile devices, and the IoT (PwC, 2022). As complex data models, urban digital twins facilitate collaborative planning and decision-making processes (Dembski et al., 2020). They represent not only a city's infrastructure and superstructure but also all the tasks performed and services delivered within it.

The primary goal of urban digital twins is to enhance the efficiency of city planning, construction, disaster response, energy management, communication, logistics, transportation, and overall urban sustainability (Deng et al., 2021). By assessing the real-time status of environmental systems, they enable optimal solutions and contribute significantly to ecological sustainability (Shahat et al., 2021).

For example, a digital replica of a city’s physical landscape can be constructed using local geographic data. This allows urban planners to analyze and predict the impact of proposed developments on air quality, mobility, water management, and building emissions with high accuracy (Yıkıcı, 2023). As a data-driven planning tool, digital twin projects provide a 3D model of the city, supporting scenario development and real-time project execution based on up-to-date information (Republic of Türkiye Istanbul Metropolitan Municipality Information Technology Department Smart City Branch Directorate, 2021).

While many smart city initiatives focus on embedding digital technologies into urban infrastructure, some perspectives emphasize the broader impact of smart cities. These perspectives suggest that smart cities improve public services and environmental quality and enhance local economic competitiveness through innovation. Additionally, they argue that smart city development should not be limited to government-led initiatives but should emerge from the collective actions of individuals and private entities leveraging smart services (José & Rodrigues, 2024).

The Istanbul Metropolitan Municipality (IMM) has adopted a strategic approach to real-time urban monitoring through a comprehensive 3D city model. This model integrates data from geographic information systems, high-resolution aerial photography, satellite imagery, and street-level panoramic images to enable proactive urban management (Republic of Türkiye Istanbul Metropolitan Municipality Information Technology Department Smart City Branch Directorate, 2021). In summary, urban digital twins play an important role in building smart, efficient city management systems. By providing a dynamic 3D virtual environment, they support urban planning, enable automation-driven decision-making, facilitate collaboration, monitor execution, assess operational outcomes, and enhance feedback mechanisms.

Digital Twin Institutions

The development of digital twins as part of urban digital twin initiatives will drive smart planning, foster significant innovations in management and services, and serve as a foundational step toward building smart cities (Deren et al., 2021). The concept of digital twins should focus on digitizing the service environment, service providers, service development processes, and service delivery mechanisms (Kumaş & Erol, 2021).

Digital twin technologies serve as critical solutions for institutions that provide services and contribute to urban infrastructure.

With the emergence of Industry 4.0 technologies, digital twin technology has made significant strides, offering substantial benefits to businesses and institutions. Its potential advantages have significantly increased its appeal. Research indicates that the market size for digital twin technology is currently valued at approximately $3.1 billion, with a predicted increase of $48.2 billion by 2026 (Leng et al. 2021).

Additionally, it is estimated that 30% of Global 2000 companies will leverage data from digital twins of products and assets to enhance product innovation and corporate efficiency, resulting in a 25% increase in operational efficiency (Bulut, n.d.).

The application of digital twins varies across industries. For instance, in the energy sector, digital twins are primarily utilized for monitoring and analytical evaluation to optimize service delivery. In the transportation sector, they serve as tools for capacity planning, transportation network optimization, and real-time monitoring of transportation assets in train stations and airports (Handan, 2021).

Ultimately, integrating institutional digital twins plays a crucial role in developing and managing smart cities. This process involves creating virtual representations of institutional duties and responsibilities, physical assets, business processes, and service offerings in a digital environment. Cities can develop and sustain a comprehensive digital twin ecosystem by establishing digital twins of institutions. This initiative represents a key policy objective, enabling institutions to harness the power of digital technology to pursue more sustainable, efficient, and inclusive smart cities that benefit both citizens and stakeholders.

Artificial Intelligence

AI to function effectively in a smart city, it must have the ability to learn from its surroundings, extract meaningful insights from collected data, handle incomplete information and uncertainty, determine the best course of action, and make autonomous decisions—potentially surpassing human capabilities in these areas. In this context, AI in smart cities is currently represented by autonomous vehicles, robotics, and the concept of the "city brain" (Cugurullo, 2020).

AI is a pivotal technology that integrates essential aspects of smart cities, encompassing urban life, government, economy, environment, and public services. AI and other advanced technologies have become powerful tools for developing optimal policies to address complex urban challenges, encompassing intelligent transportation networks, privacy and security issues, efficient energy grids, and advanced medical technologies (Szpilko et al. 2023).

The fast development of AI has significant opportunities to tackle urban challenges and increase the welfare of citizens. Key applications of AI in smart cities include smart mobility, environmental management, governance, economic development, and citizen engagement (Wolniak & Stecuła, 2024).

Moreover, AI's integration with big data analytics is proving to be a game-changer for smart cities. Utilising AI-driven data analysis, municipalities can optimise resource distribution, improve infrastructure management, and provide innovative services that respond to changing requirements (dos Santos et al., 2024).

In summary, Artificial intelligence is set to transform urban administration by analysing extensive datasets derived from sensors and social media. AI can optimize urban planning and automate task assignments through machine learning algorithms and real-time feedback. As the "brain" of the smart city, AI is the most critical component, driving efficiency, safety, and sustainability.

Automation

Automation in smart cities refers to using advanced technologies to perform tasks with minimal human intervention. This includes AI, 5G connectivity, big data analytics, the IoT, and augmented/virtual reality technologies, all of which help streamline processes and enhance productivity (Zara, 2023). By leveraging automation, cities can respond more effectively to real-time data transmitted by IoT-connected devices.

For example, automated street lighting systems use sensors to detect light and motion, ensuring that streetlights turn on only when needed and switch off during inactivity. This promotes energy efficiency and enhances urban operations' sustainability (Gomstyn & Jonker, 2023).

The global shift toward AI and automation in urban environments continues to gain momentum. Many cities in Australia and Canada are adopting AI and robotics into their infrastructure, while Moscow has also made significant advancements in this area (Golubchikov & Thornbush, 2020).

The automation in transportation alone can yield numerous benefits, including alleviating traffic congestion and reducing emissions and energy consumption, minimizing accidents and material damages, and optimizing the use of parking spaces (Lohmann & Van der Zwaan, n.d.). Ultimately, automation plays a critical role in increasing productivity, efficiency, and cost-effectiveness within smart cities. Even outside the scope of smart city initiatives, automation is already deeply integrated into urban life and will continue expanding into a growing number of services.

Integrating digital twins, AI, and automation represents a significant step toward building truly smart cities. Digital twins, which provide historical and real-time data on urban infrastructure, services, and activities, are foundational for implementing AI and automation in city management.

AI systems powered by high-capacity computing can leverage digital twins of institutions as edge computing nodes, processing vast amounts of data collected from local data centers, IoT devices, and sensors throughout the city. By continuously monitoring this data, AI can predict issues, optimize operations, and enhance decision-making processes.

Machine learning algorithms enable AI to make data-driven urban planning and management decisions. AI systems can generate task orders autonomously or with human oversight and distribute them to relevant entities. In critical situations, such as major disasters, AI can be authorized to take direct action, automating governance for rapid response and crisis management.

Automation, closely linked with AI and digital twins, streamlines routine tasks by continuously monitoring and controlling urban assets. Highly standardized processes like smart public transportation systems can be fully automated using edge computing and robotic technologies. Even complex functions like maintenance, security, and resource allocation can be automated based on real-time feedback, improving efficiency and adaptability.

Furthermore, adaptive and self-learning systems can enhance the city's responsiveness by adjusting their parameters in real-time based on evolving conditions. This synergy between digital twins, AI, and automation strengthens operational efficiency, optimizes resource utilization, and fosters the development of sustainable and resilient urban environments.

Table 1 below illustrates the physical structures and information technologies in smart cities.

Table 1: Physical Structures & Information Technologies in Smart Cities

Smart City Components	**Physical Structures, Information Technologies and Applications**
Digital Twin City	• Geographic features, including geology and climate • City infrastructure (e.g., roads, bridges) and superstructures (e.g., buildings, parks, gardens) • Utility networks (e.g., water, sewage, electricity, natural gas, fiber-optic communication systems) • IoT devices, cameras, and other sensors • Transportation, security, disaster response systems
Digital Twins of Institutions	• Physical assets of institutions • Roles and responsibilities, including regulatory information • Internal policies and business processes • Local data centers
Artificial Intelligence	• Machine learning and deep learning algorithms • Data analytics programs utilizing big data
Automation	• Automated governance processes • Edge computing technologies • Robotics applications

Smart City Management

The efficacy of smart city initiatives is driven by key factors such as management and organization, technology, administration, public context, economy, and information systems infrastructure (Khan & Zia, 2021). Among these, the technology infrastructure—comprising information and communication systems—plays a critical role in maintaining accessibility, integration, and quality of services. The core of this technological infrastructure is the digital twin city, which possesses four fundamental characteristics (Deren et al., 2021).

- Accurate Mapping – Provides a precise virtual representation of urban infrastructure.
- Virtual-Real Interaction – Ensures real-time synchronization between the digital and physical worlds.
- Software Description – Defines urban structures and operations in digital formats for analysis.
- Smart Feedback – Enables AI-driven learning and optimization for continuous urban improvements (Deren et al., 2021)

By integrating digital twins and AI and providing automation, smart cities can optimize urban management, improve resource allocation, and enhance sustainability. The fusion of these technologies represents a shift toward a fully digitized, data-driven, and self-optimizing urban ecosystem. The Table 2 below illustrates the key roles and functions of smart city components representing the smart city technologies and their applications

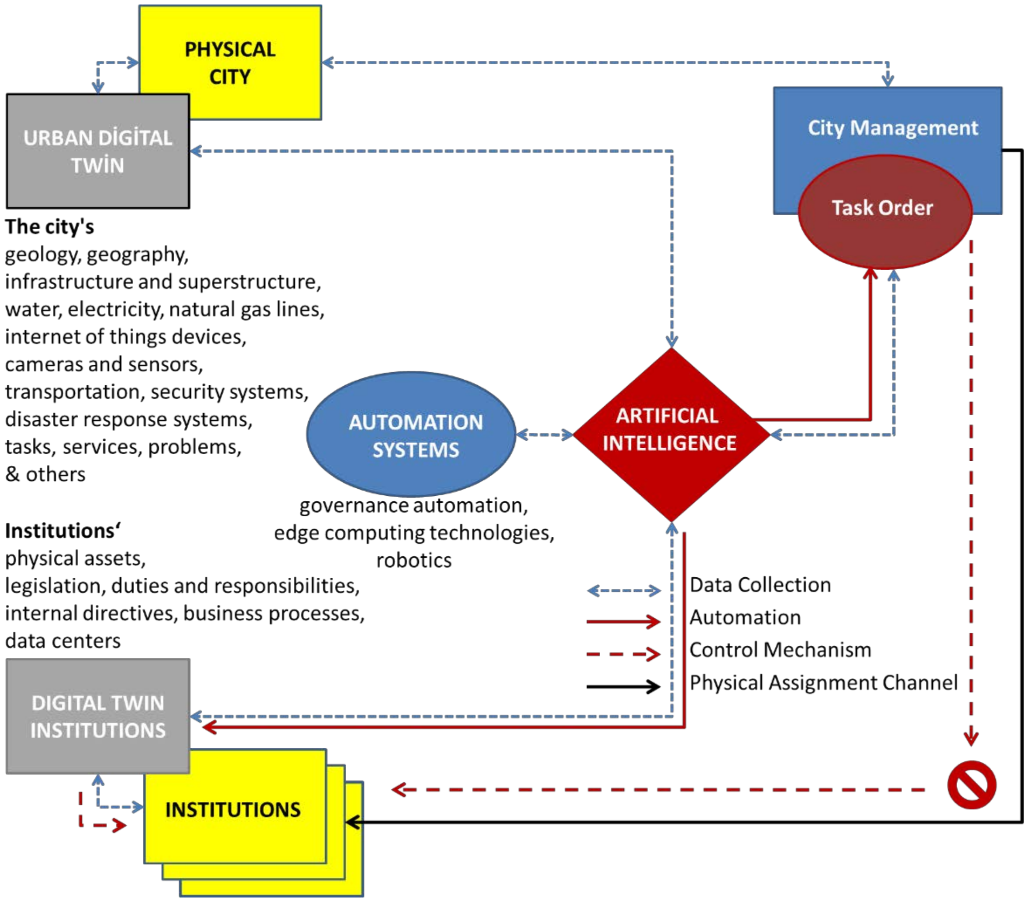
Table 2. Smart City Components, Key Roles and Functions

Smart City Components	Key Roles & Functions
Digital Twin City	• Creates a real-time and historical virtual representation of the city • Collects and integrates data from urban infrastructure, IoT devices, and sensors • Supports scenario-based planning, simulations, and predictive analytics • Enhances coordination between city departments and services

Digital Twins of Institutions	• Digitally represents an institution's physical assets, services, and processes • Enables seamless integration with the digital twin-city • Facilitates data-driven decision-making for optimized operations • Supports automation in monitoring, planning, and service delivery
Artificial Intelligence	• Processes and analyzes big data for insights and optimization • Supports predictive maintenance, demand forecasting, and emergency response • Enhances decision-making with machine learning algorithms • Automates governance and public services with real-time monitoring and control
Automation	• Reduces human intervention in routine processes • Enables smart transportation, adaptive traffic management, and smart energy grids • Supports autonomous public services, such as automated waste management and security • Enhances operational efficiency and sustainability through automated systems

Considering ideas and concepts introduced in Table 1 and Table 2, Figure 1 presents a schematic representation of the functions performed by smart city components, along with the relevant entities and data flow between them.

Figure – 1 Smart City Model and Management



In this model, AI serves as the brain of the smart city, with digital twins and data centers acting as the primary sources of information. While edge computing technologies—functioning like nerve endings—can resolve issues locally, they still transmit the full dataset to AI. AI processes data from digital twins, edge computing, and robotic applications. Governance automation then distributes electronic task orders to the relevant points. The city administration determines which tasks can be executed without additional human oversight, while tasks requiring supervision, along with their assignments and orders, are subject to approval by authorized personnel.

3. METHODOLOGY

This study employed a literature review as its primary research method. The review focused on the advantages, limitations, and advanced applications of digital twins, artificial intelligence, and automation within the context of smart cities. The analysis began with summarizing and categorizing key findings, themes, and gaps using qualitative analysis techniques such as thematic analysis and content analysis (Dehkordi et al., 2021). Additionally, observations, document reviews, professional experiences, and insights gained from the researchers' involvement in smart city projects were incorporated into the qualitative analysis.

Three research questions guided this study:

Identification of Key Information Technologies for Smart Cities

The first research question was explored through literature analysis. The review focused on identifying and synthesizing the essential information technologies used in smart cities and their critical roles in ensuring effective, economical, and efficient smart city management. Academic studies in this field were systematically examined.

Analysis of Information Processing Models of Smart Cities

The second research question aimed to provide a comprehensive overview of various information processing models conceptualized and implemented in smart city contexts in Türkiye and globally. This study identified existing models and discussions in the literature by examining the theoretical foundations, conceptual frameworks, and empirical evidence related to smart city management information processing models. A comparative analysis was conducted, focusing on real-world applications in Istanbul and Balıkesir (Türkiye) and London (United Kingdom). The study investigated the contextual factors, stakeholder dynamics, and implementation strategies influencing the adoption and deployment of these models in smart city projects.

Development of a Smart City Model for Türkiye

The third research question was addressed through a combination of literature analysis, case studies, and comparative evaluations. The study aimed to provide insights into the theoretical advantages and potential benefits of a smart city information management model tailored to public administration conditions in Türkiye. Expected outcomes, anticipated impacts, and perceived benefits of implementing a specific management model for smart cities in Türkiye were analyzed and discussed.

4. FINDINGS

Smart City Examples: Implementations of London, İstanbul, and Balıkesir

These cases explore the role of information technologies and systems in the smart city transformation of London, İstanbul, and Balıkesir, highlighting their goals and current applications in the journey toward becoming smart cities.

London

In London, a more collaborative approach is being embraced to leverage big data and smart technology in addressing both current and future challenges. Efforts are underway to mobilize the resources of government services, premier universities, and the technology sector. To guide this initiative, London has appointed its first Chief Digital Officer and established a new Smart London Board of Directors, alongside a roadmap to ensure the effective use of big data and digital technologies (Greater London Authority, 2018).

According to the roadmap, the strategy for London focuses on producing more user-designed services, launching the London Data Analytics Office program, developing a cybersecurity strategy, supporting an open ecosystem to foster innovation, planning 5G projects, expanding fiber infrastructure, enhancing WiFi networks, building next-generation smart infrastructure, promoting standards for smart technologies, increasing big digital data, and developing the computing skills and digital talent of both the workforce and citizens. Additionally, the strategy emphasizes integrating collaboration among all subsystems in London first and later collaborating with global cities (Greater London Authority, 2018).

The completion of all digital maps of England by the Ordnance Survey in 1995 (ESRI) gave London a significant advantage in terms of geographical data for its smart city journey. A recent study revealed that London was selected as the city best prepared for a smart future in Europe, earning an overall score of 73.7 out of 100 (Proptechos, n.d.). The London Data Center plays a key role in the smart city strategy, with Londoners enjoying free access to information and statistics about the city. Smart city technologies have become integral to daily life in London, with vast amounts of real-time data provided through 5G networks, a broad network of sensors, cameras, drones, robotics, and automation, all contributing to the safe management of the city (Puttkamer, 2023).

For smart city management in London, the city has advanced its digital twin, big data management, AI-driven data processing, robotics, and automation. As the work progresses, the collaboration between all subsystems has been identified as a crucial goal in creating a unified management system.

Istanbul

The implementation of the smart city governance model in Istanbul is addressed through four transformation stages: smart city management, smart decision-making, smart collaboration, and smart management. The first stage focuses on the effective and efficient implementation of the right policies without requiring changes to the existing management structure and processes. The second stage emphasizes the restructuring of decision-making mechanisms, while the third and fourth stages introduce smart management and collaboration as essential components of the transformation (Republic of Türkiye Istanbul Metropolitan Municipality Information Technology Department Smart City Branch Directorate, 2021).

Innovative technologies improve managerial rationality by utilising more accessible and precise data for decision-making and execution. Smart management embodies a novel paradigm of electronic governance that employs modern technology to link and unify information, processes, institutions, and physical infrastructure. As part of the first-stage initiatives, several bodies were established, including the Smart City Governance Platform and Coordinator, Smart City Executive Board, Smart City Advisory Council, and the Smart City Thematic Area Project Coordination Units. Additionally, the Smart City Implementation Office was set up to oversee the execution of these efforts (Republic of Türkiye Istanbul Metropolitan Municipality Information Technology Department Smart City Branch Directorate, 2021).

Studies have been launched to create a management information system for Istanbul's smart city governance to analyze data gathered from the city, create a digital twin of the city, and conduct scenario analyses based on this data.

Balikesir

In Balıkesir, the smart city journey began with adopting Geographic Information Systems solutions. A roadmap associated with GIS was developed as part of the municipality's duties and responsibilities. This led to the creation of Türkiye's first Geographic Data Regulation, which aligns with national legislation and data standards. The regulation aims to establish standard applications and define the roles and responsibilities of relevant units to manage geographic information effectively, economically, and efficiently, enabling the city to make accurate, spatially-based decisions (Balikesir Metropolitan Municipality, 2023).

In efforts to develop the smart city's management information systems, the Data Management Center was established to manage big data, with a particular focus on geographic data. Initiatives such as disaster management and the application of AI and machine learning to big data have also been launched. Around 600 out of an anticipated 3.000 data layers for the city's digital twin have been made available to the data center, with updates provided every month when not available online. The digital twin project is nearing completion for the Metropolitan Municipality (Balikesir Metropolitan Municipality, 2024).

As part of the city's real-time data-based urban management, particular attention is being paid to automation, leveraging IoT devices, vehicle sensors, smart cameras, and especially traffic management systems (Smart cities portal, n.d.).

All of these initiatives aim to enhance city management, make public services more effective and evidence-based, and enable sustainable planning and management from a unified platform. The smart city management information system will seek to make city governance more effective, sustainable, efficient, and cost-effective, addressing complex, multifaceted problems with a holistic approach (Balikesir Metropolitan Municipality, 2024).

Cities are considered smart when management can optimise the utilisation of both tangible and intangible assets, enhance inhabitants' quality of life, improve resource productivity, and address new challenges. The literature on smart cities is divided into two sub-sections. Some researchers present studies on smart cities by paying attention to the dimensions and areas of smart cities. In contrast, the other group of researchers focuses on using cross-functional organizations to perform smart city initiatives and the role and characteristics of public administrators (Michelucci et al., 2016).

The tangible assets discussed in this study are the physical city, the management structure of this city, the institutions serving the city and their physical assets, and especially information and automation technologies.

A smart city is a transformation project. The driving forces of institutional transformation achieve transformation by providing organizational and operational maturity. As strategy, market and sales, services and products, organizational design, resources, and stakeholder participation develop, organizational and operational maturity also develops (Bahner & Stroh, 2004).

Accordingly, it may be necessary to express the strategic level duties of smart city management as follows.

- Preparation of the smart city transformation strategy document (strategic plan) and obtaining the approval of all stakeholders,

- Establishing a smart city management organization in accordance with the legislation and allocating resources,
- Determination of the basic purpose and operational goals, the services and tasks to be performed, and service and task performance standards.

In the smart city management model, authorized operation and service production levels that can fulfil management functions at all levels should be established, and standardized tasks should be determined.

5. PROPOSED CONCEPTUAL FRAMEWORK

City Management Responsibility in Türkiye

This section attempts to create a model proposal on how institutions responsible for the management of cities in Türkiye can take part and play a role in smart city management.

In Türkiye, although Governors are responsible for the general administration of the province, communication between Ministries and Provincial organizations and monitoring of work, and ensuring coordination of Provincial services and duties between Municipalities and Ministry organizations (The Provincial Administration Law No. 5442/ Article 9 and 21); the management responsibility for services and duties in the city is given to Municipalities. Municipalities are responsible for a wide range of duties and services, from zoning plans to business licenses, highway and waterway transportation, urban transportation planning and construction of roads, use of water, disposal and reuse of wastewater, solid waste, environmental protection and control, surveillance of public health, safety of food supply, social facilities, social affairs and social services, support and execution of arts, sports, widespread education and cultural activities, development of agriculture, tourism, industry and trade in the city, and taking precautions and intervention against disasters when necessary. Decisions are the duties of the Municipal Councils, and execution is the duty of the Mayors. In addition, the Municipalities are responsible for digitalising the city, developing a strategic vision and strategic plan for smart city initiatives (Metropolitan Municipalities Law No. 5216/Article 7 and Municipalities Law No. 5393 /Article 18).

The 1/100,000 scale Environmental Regulation Plans published by the Ministry of Environment, Urbanization and Climate Change dictate the decisions of the Central Government regarding settlement and land use, including residential areas, industrial zones, agriculture, tourism, and transportation. Municipalities also coordinate their significant investments in the city with the Central Government through the Ministry of Environment, Urbanization and Climate Change (2018/30474 Decree Law). The tasks addressed by the Central Government under the title of disaster-resistant living spaces and sustainable environment in the 5-Year Development Plans determine targets within the scope of disaster management, urban transformation, urbanization, housing, environmental protection, urban infrastructure, regional development, rural development subheadings (Türkiye's Twelfth Development Plan 2024-2028), and these targets directly bind the Municipalities responsible for the management and execution of duties and services in the city.

According to the legislation in force in Türkiye, it is considered appropriate for the smart city upper management duties to be carried out by the Metropolitan or Provincial Municipalities in coordination with the Central Government and the Governor, the operations-level duties to be carried out by District Municipalities, Governorship Directorates, District Governorships, Metropolitan Municipality units and other equivalent institutions and organizations, and the lower-level duties and services to be carried out by the subunits of these institutions.

Therefore, it is a necessity to create digital twins of all institutions serving the city with their subunits and all physical assets. Data management centers that will provide data communication with AI for these units whose digital twins will be created should also be established.

A Smart City Model for Türkiye

The advantages of implementing a specific smart city model change based on the context and goals of each city.

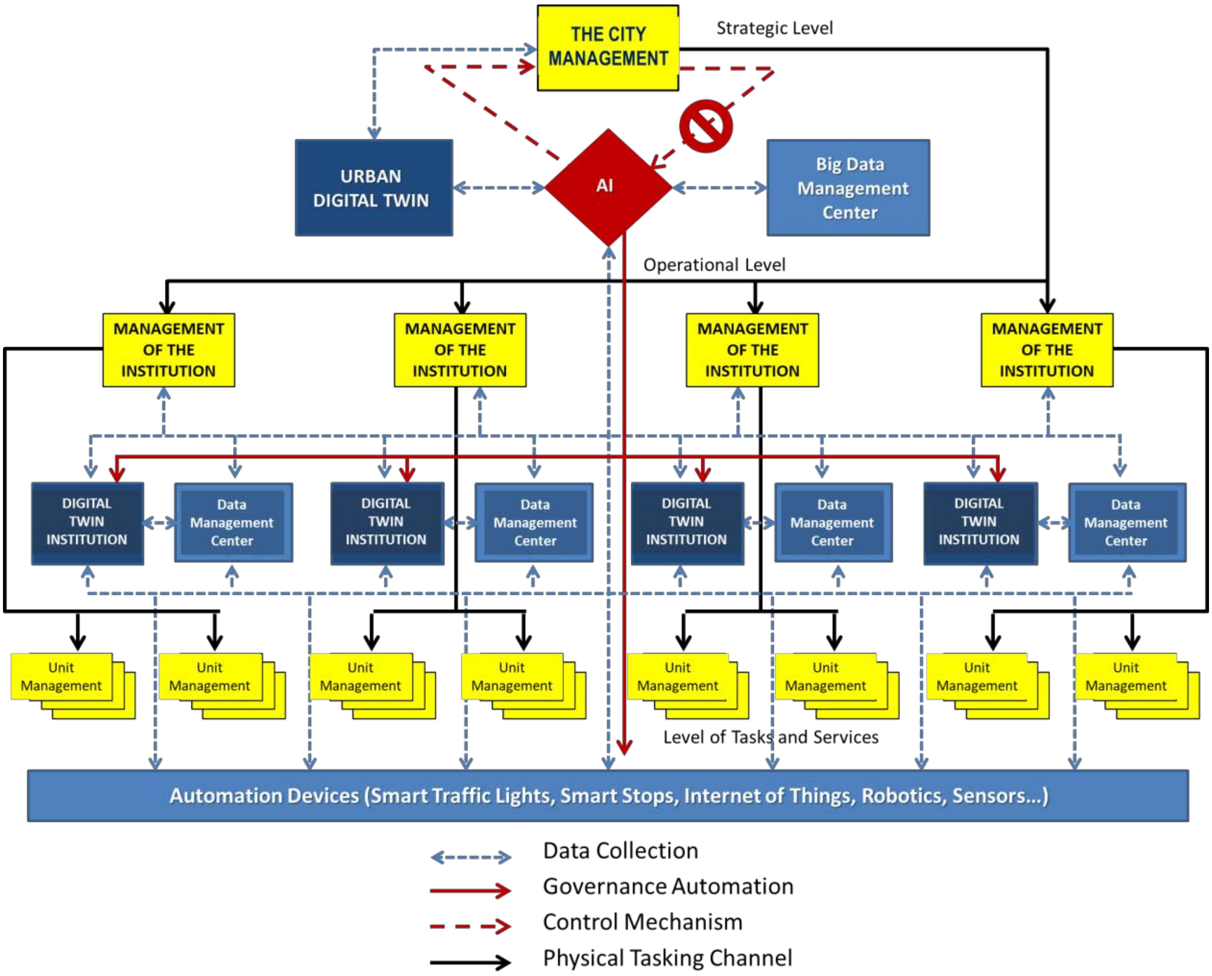
The strategic goal determined at the highest level on the path to smart cities in Türkiye is to implement Smart Cities, ensure their effectiveness and sustainability with the support of the cooperation of ecosystem stakeholders and holistic, planned and encouraging financial management system within the framework of national and local governance mechanisms, appropriate organizations, institutional architecture and legislation to which all stakeholders will contribute, and the cooperation of ecosystem stakeholders (Türkiye's Ministry of Environment, Urbanization and Climate Change 2020-2023 National Smart Cities Strategy and Action Plan).

The field of Smart Cities in Türkiye has been addressed with distributed legislation within the scope of a multi-stakeholder ecosystem and a multi-layered governance model. In this context, there is a need to foster a unified national strategic viewpoint across stakeholders supported by legislation in the field of Smart City. The common strategic perspective to be provided will ensure the coordination of Smart City studies and the sustainability of the Smart City Governance Mechanism and stakeholder organizations involved in this mechanism, which are necessary to implement policies in this field (Türkiye's Ministry of Environment, Urbanization and Climate Change 2020-2023 National Smart Cities Strategy and Action Plan).

The smart city governance mechanism is expected to be implemented with the help of information systems. In Türkiye, the city and its tasks and services can be managed centrally by the metropolitan or provincial municipalities at the strategic level. The tasks and services can be carried out effectively by institutions at the operational level and by the units of the institutions at the lower level. Advanced technologies and systems are used to make each level smart. Those technologies minimise human inadequacies with correct prioritization in the services and tasks carried out in the city and increase the speed of intervention, efficiency, productivity, accuracy and quality. With this understanding, the smart city model proposed in this study is an open system.

For the proposed model, there is a need for a competent AI established by the Metropolitan or Provincial Municipalities, digital twins and data management centers of the institutions producing services in that city, and a widespread automation structure at lower levels. A comprehensive smart city model is presented in Figure 2.

Figure 2 – A Smart City Model for Türkiye



This model provides data flow automatically at every level, and data management is performed at every level. AI, which is kept under strategic control by the upper management, optimizes planning and coordination, and cooperation efforts and can directly communicate the most appropriate course of action to the relevant parties. The city administration should control works subject to specific protocols. At every level and stage, feedback is provided between the city's digital twin and digital twin institutions and data centers, and current data is updated. Previous data is archived within data automation. Plans for routine and non-controlled jobs and assignments within this framework can be directly communicated to their responsible persons or robots as task orders.

Edge computing capabilities enable management functions (analysis, planning, ordering, control and evaluation) to be resolved at different city service levels (operations, task and service production or smart device levels). The management of some data sets in lower-level data centers, and the dissemination of such capabilities can lighten the burden of AI, which is the brain of the city.

Information systems are high-cost technologies. For example, backing up valuable current big data at geographically distant points can lead to additional costs. However, the smart city journey has no obstacle other than cost. Smart city formation is a goal that can be achieved by management information systems experts who will work patiently and devotedly for this purpose and who know their subject and technology well.

6. CONCLUSION

This study tries to shed light on the implementation of management information systems in smart cities and the approach to their implementation in Turkish Public Administration through a literature review and case studies.

According to the literature review, a smart city management information system created by combining digital twins, AI, and automation with many modern technologies will support smart cities in preparing for the future once it is established and operated. In addition, a model is proposed in this study on how digital twins, AI, and automation technologies can be used as the infrastructure of a smart city.

The answers to the determined research questions are clearly stated. The management information technologies that should be used primarily in a Smart City and the roles of these technologies in a smart city are explained. According to the determined division of labour, a ‘Smart City Model’ is presented as an open system. Accordingly, application examples in London, Istanbul and Balıkesir provinces are examined.

According to the evaluations, London has made quite good progress in the smart city journey, and cities in Türkiye, especially İstanbul and Balıkesir, continue their smart city journeys within the framework of their special conditions. In particular, the use of smart city technologies in each city and the rate of benefiting from these technologies vary according to local conditions. London is at an advanced level in issues such as digital twins, big data, and robotic automation, and Istanbul is trying to develop its work in this regard through various boards. Balıkesir, on the other hand, has prioritised the management of big data, especially geographic information systems, and has achieved partial success in AI technology, robotics and automation. The conceptual framework for implementing smart city information systems in the Turkish Public Administration has been presented in the final part of the study.

The originality of this study lies in its comprehensive analysis of how digital twins, AI, and automation can be used in smart city management. While numerous academic studies examine smart applications in cities, this study stands out by performing an analysis of how all these applications can be managed from a single source, how efforts can be combined and how efficiency, economy and high productivity can be achieved. It provides a detailed understanding of the various strategies used in the smart city field by examining the various approaches adopted in London, Istanbul and Balıkesir to promote sustainable urban development and improve citizens' quality of life.

Limitations of the Study

One of the main limitations of this article is that the evaluations were conducted for only three cities. In addition, the literature and secondary data are used for the cases of London and Istanbul. Balıkesir province was analyzed more thoroughly through observation, document review, experience and participation in existing workshops. Although these cities offer significant insights into the implementation of information technologies and systems in the development of smart cities, they constitute just a fraction of the global and national environment in Türkiye. The omission of an analysis of cities from diverse locations with varying socioeconomic conditions and cultural settings may restrict the generalisability of the results.

Future Research

Future research on smart cities could explore the long-term impacts of business strategies on sustainability, economic advancement, and social engagement, as well as integrating emerging technologies like digital twins, artificial intelligence, robotics, and automation into existing infrastructure.

Theoretical Contribution

This study presents a smart city information management model suitable for Turkish Public Administration as a conceptual framework. This framework enhances our theoretical comprehension and establishes a benchmark for further research endeavours in this domain. Furthermore, the study substantiates the theoretical framework of Turkish Public Administration legislation about governance within the context of smart cities and offers an enhanced framework. It can contribute to the experimental demonstration of the effectiveness of the proposed structure in real-world environments and to the further development and improvement of current practices.

Managerial Contribution

From a managerial perspective, the study provides a feasible model for urban policymakers, urban planners, and public sector managers involved in smart city initiatives and an evidence-based strategy proposal for urban governance. City managers can use these insights to establish assessment frameworks that guarantee the implementation of identified projects, efficient use of resources and achievement of predefined goals. The results presented by this study can create environments conducive to sustainable economic developments that encourage technological advancement and innovation in smart cities.

REFERENCES

Bahner, R. R., & Stroh, L. K. (2004). The Transformation Management Model: A Total Evaluation Route to Business Change Success. *Problems and Perspectives in Management*, *2*(4), 180–191.

Balıkesir Metropolitan Municipality (2024, 6 November). *Smart City Management era in Balıkesir* on February 15, 2024 https://balikesir.bel.tr/haberler/balikesirde-akilli-sehir-yonetimi-donemi

Balikesir Metropolitan Municipality (2023, 24 October). *Balikesir metropolitan municipality geographical data regulation.* https://balikesir.bel.tr/mevzuat accessed on 28 November 2024

Bernyukevich, T. (2023, January) *Risks of smart city projects: definition, typology, management* [AIP Conference Proceedings] Construction the formation of living environment: form-2022, Moscow, Russian Federation https://pubs.aip.org/aip/acp/article-abstract/2791/1/050043/2905427/Risks-of-smart-city-projects-Definition-typology?redirectedFrom=fulltext

Bulut, T. (n.d.) Can a digital twin of a human be created? Tevfikbulut.com

https://tevfikbulutcom.wordpress.com/wp-content/uploads/2020/07/c4b0nsanc4b1n-dijital-c4b0kizi-oluc59fturulabilir-mi-1.pdf

Chen, J. (2024). Application of Electrical Automation in Smart City. *Academic Journal of Science and Technology*, *12*(2), 2771–3032.

Cugurullo, F. (2020). Urban Artificial Intelligence: From Automation to Autonomy in the Smart City. *Frontiers in Sustainable Cities*, *2*. https://doi.org/10.3389/frsc.2020.00038

Dehkordi, A. H., Mazaheri, E., Ibrahim, H. A., Dalvand, S., & Gheshlagh, R. G. (2021). How to Write a Systematic Review: A Narrative Review. In *International Journal of Preventive Medicine* (Vol. 12, Issue 3, pp. 12–27). Wolters Kluwer Medknow Publications. https://doi.org/10.4103/ijpvm.IJPVM_60_20

Dembski, F., Wössner, U., Letzgus, M., Ruddat, M., & Yamu, C. (2020). Urban digital twins for smart cities and citizens: The case study of herrenberg, germany. *Sustainability (Switzerland)*, *12*(6). https://doi.org/10.3390/su12062307

Deng, T., Zhang, K., & Shen, Z. J. (Max). (2021). A systematic review of a digital twin city: A new pattern of urban governance toward smart cities. *Journal of Management Science and Engineering*, *6*(2), 125–134. https://doi.org/10.1016/J.JMSE.2021.03.003

Deren, L., Wenbo, Y., & Zhenfeng, S. (2021). Smart city based on digital twins. *Computational Urban Science*, *1*(1). https://doi.org/10.1007/s43762-021-00005-y

Dhingra, M., & Chattopadhyay, S. (2016). Advancing smartness of traditional settlements-case analysis of Indian and Arab old cities. *International Journal of Sustainable Built Environment*, *5*(2), 549–563. https://doi.org/10.1016/J.IJSBE.2016.08.004

dos Santos, S. C., Vilela, J. F. F., Carvalho, T. H., Rocha, T. C., Candido, T. B., Bezerra, V. S., & Silva, D. J. (2024). Artificial Intelligence in Sustainable Smart Cities: A Systematic Study on Applications, Benefits, Challenges, and Solutions. *International Conference on Enterprise Information Systems, ICEIS - Proceedings*, *1*, 644–655. https://doi.org/10.5220/0012617900003690

Golubchikov, O., & Thornbush, M. (2020). Artificial intelligence and robotics in smart city strategies and planned smart development. *Smart Cities*, *3*(4). https://doi.org/10.3390/smartcities3040056

Golubchikov, O. (2020, December). *People-smart sustainable cities*. Researchgate

https://www.researchgate.net/publication/347442407_People-Smart_Sustainable_Cities

Gomstyn, A., & Jonker, A. (2023). *What is a smart city?* Ibm. https://www.ibm.com/think/topics/smart-city

Greater London Authority (2018). *Smarter London together & the mayor's roadmap to transform London into the smartest city in the world*. https://www.london.gov.uk/sites/default/files/smarter_london_together_v1.66_-_published.pdf

Handan, İ. I. (2021, 31 Temmuz). *Top five industries that will gain the most from digital twin applications in 2021.* Dijitalis. https://dijitalis.com/blog/2021de-dijital-ikiz-uygulamalari-ile-en-buyuk-kazanc-saglayacak-ilk-bes-sektor/

Ivanov, S., Nikolskaya, K., Radchenko, G., Sokolinsky, L., & Zymbler, M. (2020). Digital twin of city: Concept overview. *Proceedings - 2020 Global Smart Industry Conference, GloSIC 2020*, 178–186. https://doi.org/10.1109/GloSIC50886.2020.9267879

José, R., & Rodrigues, H. (2024). A Review on Key Innovation Challenges for Smart City Initiatives. *Smart Cities*, *7*(1), 141–162. https://doi.org/10.3390/smartcities7010006

Karri, C., Machado, J. J. M., Tavares, J. M. R. S., Jain, D. K., Dannana, S., Gottapu, S. K., & Gandomi, A. H. (2024). Recent Technology Advancements in Smart City Management: A Review. *Computers, Materials and Continua*, *81*(3), 3617–3663. https://doi.org/10.32604/cmc.2024.058461

Khan, U. T., & Zia, M. F. (2021). Smart city technologies, key components, and its aspects. *4th International Conference on Innovative Computing, ICIC 2021*. https://doi.org/10.1109/ICIC53490.2021.9692989

Kumaş, E., & Erol, S. (2021). Endüstri 4.0'da anahtar teknoloji olarak dijital ikizler. *Politeknik Dergisi*, *24*(2), 691–701. https://doi.org/10.2339/politeknik.778934

Leng, J., Wang, D., Shen, W., Li, X., Liu, Q., & Chen, X. (2021). Digital twins-based smart manufacturing system design in Industry 4.0: A review. *Journal of Manufacturing Systems*, *60*, 119–137. https://doi.org/10.1016/J.JMSY.2021.05.011

Lohmann, R., & Van der Zwaan, S. (n.d.). *Automation and Smart Cities: Opportunity or threat?* www.2getthere.eu

Metropolitan Municipalities Law No. 5216, (2004) *Article 7, Article 9, Article 21* https://www.mevzuat.gov.tr/mevzuat?MevzuatNo=5216&MevzuatTur=1&MevzuatTertip=5

Michelucci, F. V., De Marco, A., & Tanda, A. (2016). Defining the Role of the Smart-City Manager: An Analysis of Responsibilities and Skills. *Journal of Urban Technology*, *23*(3), 23–42. https://doi.org/10.1080/10630732.2016.1164439

Municipalities Law No. 5393, (2005) *Article 18* *https://www.mevzuat.gov.tr/mevzuat?MevzuatNo=5393&MevzuatTur=1&MevzuatTertip=5*

Presidential Decisions (2018). *2018/30474 Decree Law* https://www.resmigazete.gov.tr/eskiler/2018/07/20180710.pdf

Presidency of the Republic of Türkiye, Strategy and Budget Directorate (2023). *Türkiye's Twelfth Development Plan (2024-2028)* https://www.sbb.gov.tr/wp-content/uploads/2023/12/On-Ikinci-Kalkinma-Plani_2024-2028_11122023.pdf

Proptechos (n.d.). *These cities are best prepared for a 'smart city' future. technology is developing faster than ever before. But are our cities keeping up?* https://proptechos.com/smart-city-index/

PwC (2022). *How digital twins can make smart cities better.* https://www.pwc.com/m1/en/publications/documents/how-digital-twins-can-make-smart-cities-better.pdf

Puttkamer, L. (2023, 29 Jun). *Smart city london: europe's smartest city.* Bee smart city.

https://www.beesmart.city/en/smart-city-blog/london-europes-smartest-city

Republic of Türkiye Istanbul Metropolitan Municipality Information Technology Department Smart City Branch Directorate. (2021) *2030 istanbul smart city strategic plan.* *https://www.akillisehir.istanbul/wp-content/uploads/2024/03/2030_Istanbul_Akilli_Sehir_Stratejik_Plani.pdf*

Republic of Türkiye Ministry of Environment and Urbanization (2019). *Türkiye's Ministry of Environment, Urbanization and Climate Change 2020-2023 National Smart Cities Strategy and Action Plan* *https://www.akillisehirler.gov.tr/wp-content/uploads/EylemPlani.pdf*

Roth, Z., & Incera, M. (2024, May 18). *The Rise of AI-Powered Smart Cities*. https://www.spglobal.com/en/research-insights/special-reports/ai-smart-cities

Shahat, E., Hyun, C. T., & Yeom, C. (2021). City digital twin potentials: A review and research agenda. In *Sustainability (Switzerland)* (Vol. 13, Issue 6). MDPI AG. https://doi.org/10.3390/su13063386

Smart cities portal (n.d.) *National smart cities open data portal launched* https://www.akillisehirler.gov.tr/2023/05/15/ulusal-akilli-sehirler-acik-veri-portali-acildi/ accessed on 28 November 2024

Szpilko, D., Naharro, F. J., Lăzăroiu, G., Nica, E., & de la Torre Gallegos, A. (2023). Artificial intelligence in the smart city - a literature review. *Engineering Management in Production and Services*, *15*(4), 53–75. https://doi.org/10.2478/emj-2023-0028

The Provincial Administration Law No. 5442, (1949) *Article 9, Article 21* *https://www.mevzuat.gov.tr/mevzuat?MevzuatNo=5442&MevzuatTur=1&MevzuatTertip=3*

Trindade, E. P., Hinnig, M. P. F., da Costa, E. M., Marques, J. S., Bastos, R. C., & Yigitcanlar, T. (2017). Sustainable development of smart cities: a systematic review of the literature. *Journal of Open Innovation: Technology, Market, and Complexity*, *3*(3), 1–14. https://doi.org/10.1186/S40852-017-0063-2

Türkiye's Twelfth Development Plan (2024-2028). https://www.sbb.gov.tr/wp-content/uploads/2023/12/On-Ikinci-Kalkinma-Plani_2024-2028_11122023.pdf

Wolniak, R., Gajdzik, B., Grebski, M., Danel, R., & Grebski, W. W. (2024). Business Models Used in Smart Cities—Theoretical Approach with Examples of Smart Cities. *Smart Cities*, *7*(4), 1626–1669. https://doi.org/10.3390/smartcities7040065

Wolniak, R., & Stecuła, K. (2024). Artificial Intelligence in Smart Cities—Applications, Barriers, and Future Directions: A Review. *Smart Cities*, *7*(3), 1346–1389. https://doi.org/10.3390/smartcities7030057

Yang, S., Jahanger, A., & Usman, M. (2024). Examining the influence of green innovations in industrial enterprises on China's smart city development. *Technological Forecasting and Social Change*, *199*, 123031. https://doi.org/10.1016/J.TECHFORE.2023.123031

Yıkıcı, A. (2023). Dijital İkiz Şehir Fenomeni: Dünyadan Örnekler ve Türkiye'deki Yönelimler. *Kent Akademisi Dergisi*, *16*(1), 138–163. https://doi.org/10.35674/kent

Zara S. (2023, February 22). *FIVE Automation Technologies for Smart Cities*. https://kahedu.edu.in/five-automation-technologies-for-smart-cities/

Paper #43

Title: Advancing Maritime Competitiveness: Insights into Digital Ports and Maturity Models

Authors: Gülşen Akman, Berrin Denizhan, Ali İhsan Boyacı, Elif Yıldırım

Affiliations: Kocaeli University; Sakarya University

Abstract:
This study explores how digital technologies enhance the competitiveness and sustainability of ports. It focuses on digital maturity models as tools for evaluating transformation and guiding improvements. By analyzing key technologies and case studies, the paper identifies challenges, opportunities, and strategic pathways for digital port development.

Keywords: Digital ports, digital transformation, maturity models, maritime logistics

Paper #46

Title: Handling Digital Transformation as a Wicked Problem or Not: A Case Study

Authors: Mehmet Selim Derindere, Zehra Özsürünç, Sevinç Gülseçen

Abstract:
This paper examines digital transformation (DT) as a complex and often misunderstood process. It argues that many DT initiatives fail due to a technical mindset that overlooks human, organizational, and contextual factors. Using a case study and action research, the authors explore how problem setting, reflective practice, and collaborative inquiry can better address DT's wicked problem nature.

Keywords: Digital Transformation, Wicked Problems, Problem Setting, Organizational Change, Collaborative Research

Paper #50

Title: The Assessment of Digitalisation and the Use of Artificial Intelligence in a Small and Medium-Sized Enterprise

Author(s): Müberra Allahverdi and Fatma Ebru Yıldız

Affiliation: Ankara Yıldırım Beyazıt University, Türkiye

Abstract:
This paper assesses the digital maturity and AI use in a Turkish SME using North et al.'s (2020) maturity model. Through interviews and document analysis, it identifies gaps in strategic planning, data infrastructure, and digital culture. The study concludes that although the SME has digital potential, a structured roadmap is essential for transformation.

Keywords: Digital Maturity, Artificial Intelligence, SMEs, Digital Transformation, Case Study

Paper #53

Title: Process Mining: Theoretical Foundations and Practical Contributions

Authors: Elif Suzen and Selcuk Cebi (Yildiz Technical University)

Abstract:
This paper presents a comprehensive literature review on process mining, focusing on its theoretical foundations and practical applications. It explores the three main approaches—discovery, conformance checking, and enhancement—supported by real-world use cases from 1998 to 2024. By analyzing 72 academic works across various domains, the study highlights the evolution of process mining and its role in business process optimization. It also examines the integration of emerging technologies like machine learning and explainable AI to enhance predictive capabilities and decision-making.

Keywords: Process Mining, Business Process, Event Logs, Data Mining, BPM Lifecycle

Paper #52

Title: Analysis of Sentiment in Hotel Comments with Natural Language Processing

Author(s): Emrah Aydemir and Alper Ay (Sakarya University)

Abstract:
This study uses Natural Language Processing (NLP) to analyze sentiment in online hotel reviews. It compares various machine learning algorithms to classify positive and negative sentiments, helping hotels better understand customer feedback. The paper highlights the impact of review content on business insights and customer satisfaction.

Keywords: Sentiment Analysis, Hotel Reviews, NLP, Machine Learning, Customer Feedback

A Systematic Review Integrating the Perspectives of Artificial Intelligence for Sustainability and Sustainability of Artificial Intelligence

Abstract

While artificial intelligence (AI) technologies offer significant opportunities to accomplish sustainable development goals (SDGs), they also bring ethical, environmental, and economic challenges. In this study, a systematic literature review was conducted in two main dimensions, namely the contributions of AI to sustainability and the ensuring of the sustainability of AI. Using the PRISMA methodology, 167 articles were identified from Scopus, Google Scholar, and Web of Science databases, and 81 articles were subjected to detailed review according to the eligibility criteria. The findings show that the contributions of AI to sustainability are concentrated in the fields of economy and industry, especially within the scope of the sustainable development goals (SDGs). However, there is insufficient research on the impacts of AI on environmental and social sustainability.

On the other hand, issues such as energy consumption, carbon emissions, and environmental impacts of data centers were addressed under the sustainability of AI, and the need to integrate AI with green technology was emphasized. The study results show that AI should be addressed with a more holistic approach within the sustainability framework. In this context, ethical AI management, reducing environmental impacts, and ensuring social equality stand out as critical issues.

Keywords: Artificial Intelligence, Sustainability, Sustainable AI, Sustainable Development Goals

1.Introduction

Artificial intelligence (AI) has been playing a crucial role in environmental, economic and social sustainability issues in recent years with the acceleration of digitalization and automation. Today, AI is widely used to increase the effectiveness of business processes, optimize energy management, improve healthcare services and create sustainable production models (Wang, Li, et al., 2024). However, these opportunities offered by AI also bring ethical, environmental and economic challenges. In the literature, the impacts of AI on sustainability are addressed under two main headings: (1) how AI contributes to sustainable development and (2) whether AI itself is sustainable (Rohde et al., 2024). The contributions of AI to sustainable development are especially addressed within the framework of sustainable development goals (SDGs). Among the 17 SDGs determined by the United Nations, AI has been shown to have major impacts, especially in the areas of industry, innovation and infrastructure 'SDG 9' and economic growth and employment 'SDG 8' (Sætra, 2021). However, there are not enough studies on the effects of AI on social sustainability, reducing inequalities, and environmental sustainability (Nasir et al., 2023).For example, no comprehensive framework has been established on the impacts of AI on SDG 5, 'Gender Equality', SDG 10 ', Reducing Inequalities' and SDG 13 ', Climate Action' (Sætra, 2021). This situation shows that the contribution of AI to global sustainability goals should be addressed with a more comprehensive perspective. On the other hand, whether AI itself is sustainable has become an increasingly debated topic. Studies show that AI systems cause environmental problems such as high energy consumption, carbon emissions, and data management difficulties during their development and implementation (Bolón-Canedo et al., 2024). Since training deep learning models requires a large amount of computational power, energy consumption and greenhouse gas (GHG) emissions increase meaningfully (Kopka & Grashof, 2022). In this context, solutions such as energy-saving algorithms, green data centers, and environmentally friendly hardware are emphasized for the development of sustainable AI applications (Lewerenz et al., 2024; Pal et al., 2024).

Considering the opportunities offered by AI in terms of sustainability and the risks it brings, the main purpose of this study is to provide an inclusive analysis to understand the contributions of AI to sustainable development and how the sustainability of AI can be achieved. In the study, research conducted in Scopus, Google Scholar, and Web of Science databases was examined using a systematic literature review (PRISMA methodology), and 81 academic articles on AI and sustainability were analyzed in detail.

2. Research Methodology

2.1. Systematic Literature Review

In this study, we employed the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) methodology for our systematic literature review, as it provides a comprehensive and structured framework for reviewing the literature. For this systematic review, we conducted article searches using the Scopus, Google Scholar, and Web of Science databases. To conduct our research, we utilized a set of keywords to search within article titles and keywords across the selected databases. To identify literature related to "AI" and "sustainability," we searched for the terms "sustainable AI" and "sustainable artificial intelligence." Using these terms introduced certain limitations, as some generic articles related to "sustainably," "sustainability," or "sustainable development" may have been overlooked. However, this approach resulted in a total of 167 articles. All retrieved papers were manually examined to ensure their relevance to the subject, and any unrelated articles were excluded. Conference papers, books, and conference reviews were not considered for this literature review. As a result, our research included 45 publications on the Sustainability of AI and 36 publications on AI for Sustainability, totalling 81 papers.

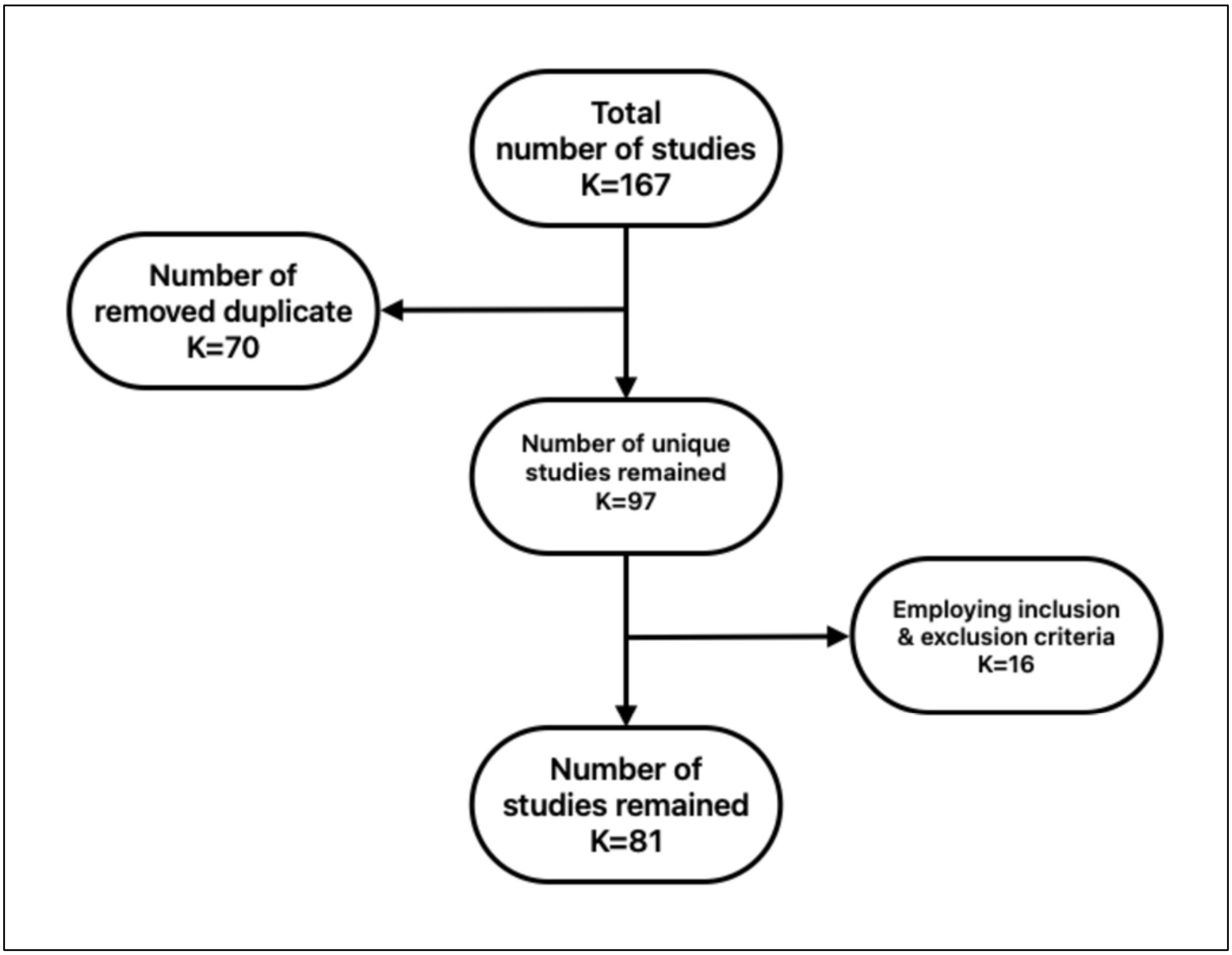


Figure 1. The procedure of the systematic review.

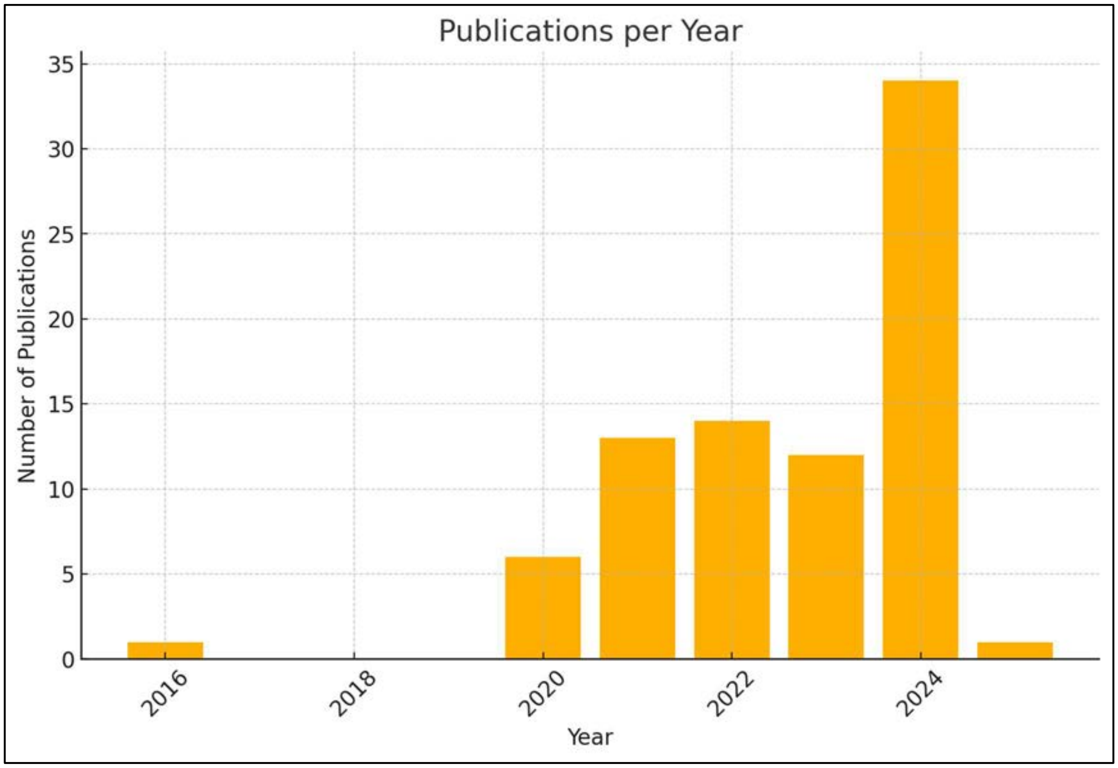


Figure 2. Number of publications per year.

3. Findings

We have determined two different dimensions on the publications, ‘AI for Sustainability’ and ‘Sustainability of AI’. In the AI for Sustainability section, two distinct clusters emerged while examining studies: Sustainable Development Goals (SDGs) and Others**.** Others contain a wide range of subtopics such as production, agriculture, education and urbanization (Fig.3). Rohde et al. (2024) offered a framework to recognize the life-cycle perspective on AI systems in six phases and four dimensions. Our study used that framework to conceptualize the Sustainability of AI dimension. In the clustering phase, some studies have been defined in more than one dimension because of the nature of the research.

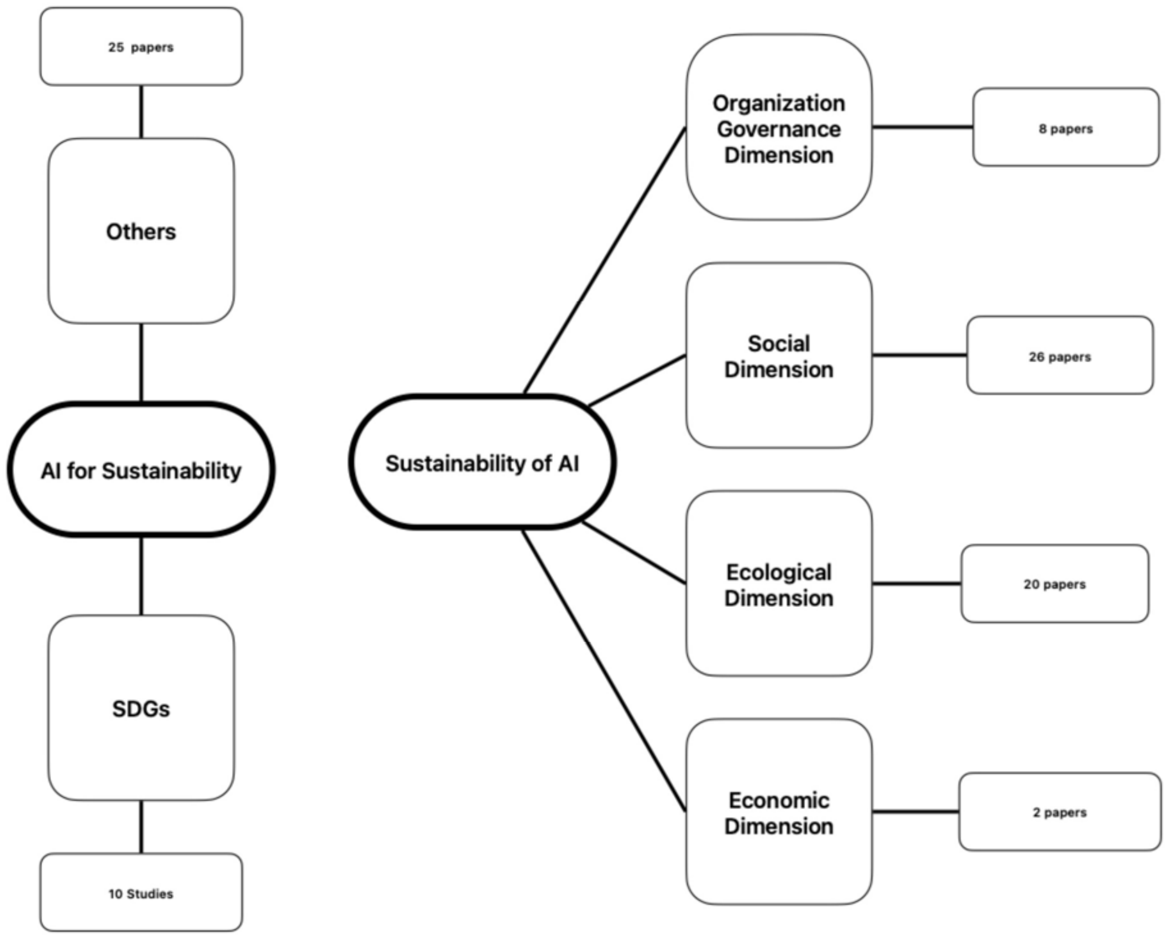


Figure 3. Distribution of topics.

3.1. AI for Sustainability

3.1.1. Sustainable Development Goals

The 17 Sustainable Development Goals (SDGs) defined by the United Nations Agenda 2030 create a global blueprint scheme and instrument for peace and prosperity worldwide (UN, 2015). The potential use for AI in SDGs to clarify the goals and enhance the efficiency while establishing the progress has been examined in various aspects. SWOT analysis (Strengths, Weaknesses, Opportunities and Threats) has been applied based on current literature by Palomares et al. (2021) to understand the efforts in applying AI technologies to SDGs. Palomares et al. (2021) offer 5 key elements and priorities for achieving SDGs. Reliable and well-managed data for AI supports collaboration between science, industry, and government, facilitating technology transfer and the adoption of coordinated action strategies tailored to each country's context. Additionally, it enables the development of alternative standards to advance the attainment of Sustainable Development Goals (SDGs), offering key lessons learned from the COVID-19 pandemic (Palomares et al., 2021). Sætra (2021) created a framework for classifying the SDGs in terms of AI impact. The framework indicates direct and indirect effects on SDGs with high, medium and minor impacts (Sætra, 2021). While AI has profoundly influenced SDG 8 and SDG 9, triggering major ripple effects, SDG 3, 4, 11, and 16 have experienced similar consequences with a moderate AI impact, whereas SDG 5, 10, and 13, despite their medium AI influence, have only faced minor ripple effects (Sætra, 2021). On the other hand, indirect effects with high impact were determined on SDGs 1,2 and 12; AI had a minor impact on SDGs 6,7,14,15 and 17 (Sætra, 2021). SDG-Intense Evaluation (SDGIE) framework aims to create new approaches to advance the SDGs was introduced (Steingard et al., 2023). Based on the SDGIE framework, the SDG Impact Intensity Model (SDGIIM) was established, and SDGIIM was applied to the specific domain of the academic journal rating system as a case study (Steingard et al., 2023). The application of SDGIIM, as proposed by Steingard et al. (2023), was extended to textual datasets from various sectors and disciplines. A systematic literature review was directed to define the incorporation of AI into sustainability efforts using a holistic framework by (Kulkov et al., 2024). The study has offered a wide-ranging exploration of the organizational, technical and processing aspects (Kulkov et al., 2024). In organizational aspects importance of strategic arrangement, human capital development and stakeholder engagement were highlighted; in technical features, the selection and usage of AI, data management and ethical concerns were underlined as crucial factors and in processing aspects, business process transformation, change management and continuous development were identified as key elements in leveraging AI for sustainability (Kulkov et al., 2024). The effect of AI on sustainable development during urbanization across 51 countries was explored using panel data (Wang, Zhang, et al., 2024). The study offers three dimensions for AI's effects on sustainable development: AI R&D innovation which has the greatest influence, followed by AI infrastructure and AI market advantage has the smallest impact (Wang, Zhang, et al., 2024). The relationship between urbanization and sustainable development was examined, and policies were recommended to governments (Wang, Zhang, et al., 2024). Similarity-matching methods were used to reveal new trends and investigate the correlation between AI-related document data and SDGs (Nasir et al., 2023). Their analysis highlighted that all datasets were more worried about SDGs regarding the Economy, limited contribution to Society, and almost abandoning the Environment (Nasir et al., 2023). Schoormann et al. (2023) discussed how Information Systems (IS) research presently makes use of AI to increase sustainable development. Gill and Germann (2022) suggested a conceptual and normative methodology for AI governance to enable progress on the SDGs. The study highlighted the major gaps in AI governance for human rights; the layers have to be associated with communities and networks (Gill & Germann, 2022). The crucial implication to the field is from 'command and control' to 'connect and cooperate' shift (Gill & Germann, 2022). Truby (2020) examined the usage of AI and possible harms to the SDGs. The study argued about AI governance frameworks must require a benefit to the SDGs and well-designed regulations have to be applied to the Big Tech's (Truby, 2020).

The SDGs were analyzed and inspected in different aspects of the use of AI. The important lack in the current literature is the social and environmental use of AI for SDGs. In contrast, there is an abundance of economic use of AI for SDGs. The AI governance and ethical considerations were mentioned frequently.

3.1.2. Others

Artificial intelligence (AI) applications' usage is increasing day by day all around the world. There is a quick adaption to AI usage in sectors like construction, healthcare, energy, agriculture, and logistics. Research shows that AI usage in Urbanization will also be so widespread. AI usage is increasing the efficiency of processes and sustainable business transformation processes are getting more powerful with AI usage. The study of Seo et al. (2024) also shows new trends like cloud computing are using AI, and as a result, resource optimizations and cost reductions come together. 35 publications were listed below the 'AI for Sustainability' dimension in this research, and 25 of them are listed as 'Others'. Main Dimensions and related studies are listed in Table 1.

Table 1

Other dimensions of 'AI for Sustainability' based on different fields of application

Dimension	Studies
Sustainability	(Bossert & Hagendorff, 2023; Bracarense et al., 2022; Shang et al., 2024)
Businesss	(Di Vaio et al., 2020; Gupta et al., 2023; Sipola et al., 2023)
Education	(Strielkowski et al., 2024)
Production	(Walk et al., 2023)
Logistics	(Chen et al., 2024)
Healthcare	(Daiju et al., 2024; Biplov et al., 2024; Sen et al., 2024)

Agriculture	(Mushtaq et al., 2024; Nie et al., 2022; Linaza et al., 2021)
Food	(Marvin et al., 2022)
Energy	(Tanveer et al., 2021; Saheb et al., 2022)
Construction	(Adewale et al., 2024; Elmousalami et al, 2024)
Urbanization	(Otello & Federico, 2024); Yigitcanlar et al., 2021; Sharma et al., 2021; Yigitcanlar & Cugurullo, 2020)
Cloud Computing	(Cheongjeong et al., 2024)

Sustainability

There are many studies and research on artificial intelligence (AI) and sustainability. At this point, research on the contributions of AI for sustainability and also the threats that AI brings to sustainability. Bibliometric analysis of Bracarense et al. (2022) regarding the today and future of AI and sustainability has shown that the motor subjects pushing the research regarding AI for sustainability are usually related to renewable energy, energy efficiency and smart grid. In addition, the analysis of Bracarense et al. (2022, p.1) has revealed that AI for sustainability has five shortcomings which are "*overreliance on ML; lack of study on human responses to climate crisis mitigation strategies, lack of performance measurement; lack of research about how cybersecurity risks may impact sustainable development efforts; and lack of research about the adverse impact of AI development on the environment*". Shang et al. (2024) investigate AI and energy efficiency improvements that significantly contribute to carbon neutrality in their study, and they emphasize the importance of investing in green technologies and a skilled workforce in AI for sustainability. Bossert & Hagendorff (2023) argue for non-anthropocentric sustainable AI frameworks incorporating animal welfare and interspecies justice. The study critiques anthropocentric AI, puts forth the shortcomings of sustainable development and sustainable AI, and pushes for the inclusion of non-human interests.

Business

The increase in the usage of digital technologies and, as a result, easiness of saving and reaching data brings some benefits together. Data is one of the vital factors in decision-making in today's world, and the usage and importance of data are increasing in strategic management functionalities of companies. As a result of this, companies find it logical to invest in digital tools and digital transformation. At this point, conducting analyses using artificial intelligence applications puts companies one step ahead. The article of Sipola et al. (2023) investigates and argues the benefits of AI applications in advancing sustainability with its three dimensions: ecologically, socially and economically. For this aim, twenty-five companies in Finland and their last five annual financial reports are used as research data. Thirteen enterprises indicated that at least one dimension of AI is adopted by these enterprises, and research also shows that companies are dominantly adopting the social and ecological dimensions of sustainability. Gupta et al. (2023) investigate the role of AI in sustainable entrepreneurship, and a positive correlation between AI and environmental development in sustainable entrepreneurship is explored. This study also shows AI usage has a leverage effect in sustainable business models. The bibliometric analysis of Di Vaio et al. (2020) also explores the positive contribution of AI on sustainable business models and resource management, but also the ethical and social challenges faced. Another point, Di Vaio et al. (2020) emphasizes is the importance of knowledge management in AI-driven business sustainability.

Education

The article by Strielkowski et al. (2024) discusses how AI can be used to leverage education activities to enhance student engagement and performance. Adaptive learning assessment systems with the use of AI to optimize learning experiences for individual students is pioneer usage of these. How engagement of students can be increased via analyzing the data on student interactions and using adaptive learning technologies and taking actions according to the feedback from AI tools is discussed in this article.

Production

One of the most widely usage of AI is the production area. With the Industry 4.0 revolution and IoT integrated systems usage increase in production areas, bring to the benefit of saving and using various valuable data for analysis. The utilization of AI, machine learning, and deep learning algorithms in production processes has enhanced the efficiency of leveraging existing data for forecasting and decision-making. Walk et al. (2023) illustrate how sustainability in production can be enhanced through the use of sustainable smart product-service systems, which leverage deep learning-based computer vision, exemplified by the detection of product wear states. Outputs of this study also show sustainable smart product-service systems usage has possible improvements in environmental sustainability.

Logistics

With global concerns regarding climate change, diminishing resources, and social welfare, sustainable logistics, which are getting more critical than before, require taking care of environmental challenges, reducing climate change and sustainability. The AI usage practices in logistics optimization have also an increasing trend with this aim. Chen et al. (2024) reviewed the integration of AI in sustainable logistics optimization in their article to demonstrate the best practices, trends and also key challenges with examples from the real world. The importance of AI-driven approaches to enhance sustainable logistics and the crucial role of AI-powered predictive analytics is emphasized in the article. Adaption to the responsibilities of each stakeholder to achieve green supply chain management dimensions; green design, green purchasing, green transformation, green logistics, and reverse logistics can create a locomotive effect for sustainability. And also low-emission transportation models and the usage of renewable energy resources can also support environmental sustainability. The article also advocates for the increased adoption of emerging trends such as real-time data analytics, blockchain, and autonomous systems to enhance sustainable solutions in logistics Chen et al. (2024).

Healthcare

Studies in healthcare are mainly concentrated on enhancing healthcare via using AI. Ueda et al. (2024) analyze the environmental impact of AI in healthcare, emphasizing energy consumption, carbon footprint, and electronic waste. Additionally, he explores potential solutions, including energy-efficient AI models, green computing, and the integration of renewable energy, while discussing policy frameworks and best practices to promote sustainable AI deployment in the industry. The article highlights the importance of prioritizing sustainability and environmental responsibility as the healthcare industry increasingly adopts AI technologies. By integrating sustainable AI practices, the industry can set an example of how advanced technologies can be leveraged to benefit both human health and the environment. In another study, Paneru et al. (2024) examine the trained Support Vector Machine (SVM) model, which is used to predict a patient's health status based on data from pulse sensors, temperature sensors, and other relevant readings. The SVM model is recognized for its high accuracy and low variability, making it well-suited for consistent patient health monitoring. Its predictions can play a crucial role in early detection and timely intervention in healthcare settings. Sen et al. (2024) trained a large language model (LLM), ERG-AI, using a machine learning pipeline to generate occupational health assessments and recommendations based on raw wearable sensor data. ERG-AI provided insights into the confidence level of posture predictions, aiding decision-making and identifying areas for model improvement (Sen et al., 2024). The integration of advanced AI techniques in occupational health enhances workplace ergonomics and overall well-being.

Agricultural

Studies under this theme mainly considered how AI can be used for sustainable food production and to increase efficiency. Mushtaq et al. (2024) focus on AI's integration in wheat breeding, enhancing efficiency and sustainability in crop selection, and it is seen that AI usage accelerates breeding cycles, improves yield prediction, and enhances disease resistance. Nie et al. (2022) investigate AI applications in agriculture and deeply focus on the use of digital twins for sustainability. Survey results explore that digital twins enhance AI applications in agriculture for sustainability and efficiency. Linaza et al. (2021) highlight the accessibility of agricultural data and its possible use in decision making to deliver insights into complex systems. Like in other AI studies, data availability in AI studies in agriculture is crucial. These datasets can be gathered from various sensor sources, including machines, remote sensing technologies (such as satellites and drones), as well as soil, weather, and other existing data sources (Linaza et al., 2021). Accurate data on the spatial and temporal variability of soil and plant parameters helps optimize resource use by reducing inputs such as seeds, water, pesticides, and fertilizers, thereby contributing to sustainability.

Food

In addition to sustainable agricultural activities, food security and control are also another critical usage area of AI for sustainability. The review by Marvin et al. (2022) explores how digitalization and AI can support a sustainable food system. Studies in this area have influenced the roles and relations of the actors throughout the complete value chain, from farmers to consumers. Sensors and IoT can be utilized to predict actual product quality through predictive models, enabling early detection of potential food safety risks. This allows swift interventions to mitigate hazards, enhancing food safety and quality control.

Urbanization

Urbanization and its relationship with artificial intelligence emerge as one of the other most discussed dimensions and it also deals with different dimensions of urbanization within itself. Yigitcanlar and Cugurullo (2020) examine the function of AI in smart and sustainable cities. The study emphasizes balancing AI with social, environmental, and economic factors in city planning and policymaking. One of the following studies by Yigitcanlar et al. (2021) examines the fundamental shortcomings in mainstream AI system conceptualization and introduces the concept of "green sensing," which encompasses both physical and virtual green sensing. This approach aims to support triple-bottom-line sustainability, addressing social, environmental, and economic factors. The article also emphasizes the need for integrated AI approaches to further advance smart city transformation. In the study of A. Sharma et al. (2021) AI and Blockchain Integration for Sustainable Smart Cities is discussed and how combining AI and blockchain can optimize resource usage and ensure data security in smart city ecosystems is highlighted. One another study analyses urban studies philosophically, and Palmini and Cugurullo (2024) discuss the juxtaposition of smart and eco-urbanism that reveals philosophical contradictions for sustainable urban AI. These studies show that AI for sustainability can be considered in various improvement areas in urbanization.

On the other hand, balancing AI with social, environmental, and economic factors in city planning and policymaking is also critical.

Energy

When global energy consumption, requirements and resources are investigated, energy saving and energy usage efficiency is one of the hot topics of the world. As a result of this, since AI is used to increase efficiency in all areas, the use of AI in the energy sector for sustainable energy is also critical. Ahmad et al. (2021) examine the transformative role of AI in the energy sector, highlighting its applications in solar and hydrogen power generation, supply-demand management, and operational optimization, while emphasizing its impact on big data handling, cybersecurity, and smart grid efficiency, ultimately calling for regulatory adaptability to ensure competitiveness in the evolving digital energy market. This study highlights AI as a crucial enabler of the evolving, data-driven energy industry, serving as a powerful tool to enhance operational performance and efficiency in an increasingly competitive landscape (Ahmad et al., 2021). In another study by Saheb et al. (2022), sustainable AI and energy are explored to gain a deeper understanding of how AI can be integrated to promote sustainability in the energy sector. The study identifies eight key topics related to sustainable AI for energy: sustainable buildings, AI-based decision support systems (DSSs) for urban water management, climate artificial intelligence, Agriculture 4.0, the convergence of AI with IoT, AI-based evaluation of renewable technologies, smart campuses and engineering education, and AI-based optimization (Saheb et al., 2022).

Construction

AI usage in the construction sector is also so beneficial, and it also contributes to the sustainability of urbanization, global energy consumption and greenhouse gas emissions. Adewale et al. (2024)

discuss the potential usage areas of AI in building lifecycle, design, construction and maintenance operations. The usage of AI applications can bring data-driven analysis and provide real-time insights into the decision-making process. However, there can be some challenges during AI adoption and implementation, and cost and data security risks should also be considered. Elmousalami et al. (2024) examine the Automated Cost-Duration Variance Prediction (CDVP) system, which is used by project managers for budget and time forecasting. As discussed in the article, given that project investments account for a major portion of the world's (GDP), sustainability in construction projects is becoming increasingly crucial. Comprehensive prediction frameworks with machine learning algorithms that support data-driven decision-making approaches are required for construction projects. Elmousalami et al. (2024) also emphasize taking into consideration the carbon emissions as a performance condition in selecting the algorithms.

Cloud Computing

The studies show that each cloud service model has different challenges and opportunities for AI optimization. Seo et al. (2024) explore the necessity of AI in promoting the sustainable use of cloud service models, including IaaS, PaaS, and SaaS. The study demonstrates how AI-driven strategies can enhance sustainability and economic efficiency in cloud computing by optimizing resource management and scalability. The combination of AI in cloud resource management increases operational efficiency while also contributing to cost savings.

3.2. Sustainability of AI

3.2.1. Organization Governance Dimension

Artificial intelligence (AI) can significantly transform organizational governance, strengthening critical elements such as accountability, transparency, and efficiency (Nishant et al., 2020). AI-powered governance models can help companies and public institutions develop sustainable policies by enabling data-driven decisions (Rohde et al., 2024). However, for this transformation to be successful, ethical and legal regulations must be strictly implemented. In particular, it is of great importance to consider issues such as environmental management, corporate responsibility, and employee rights in AI applications (Alshahrani et al., 2024). Integration of AI in corporate governance procedures can support companies in achieving their sustainability goals. AI-based solutions have great potential, especially in reducing carbon footprint, increasing green energy use and making environmental impact analyses more accurate (Raman et al., 2024). However, systematic assessment mechanisms are needed for the effective implementation of sustainable AI in organizations. Frameworks that include sustainability indicators and performance measures should be developed to measure and monitor the continuing sustainability of AI applications (Rohde et al., 2024). One of the greatest advantages of AI in corporate governance is that it strengthens accountability and responsibility mechanisms (Zhao, 2024). However, strengthening ethical and legal frameworks in this process is a critical requirement for the spread of sustainable AI applications (Zhao, 2024). Especially in large-scale corporate systems, AI-supported decision-making mechanisms contribute to optimizing resource management and promoting sustainable growth (Tabbakh et al., 2024). Although AI is primarily utilized in the private sector, its application extends to public administration as well. AI-based governance in the public sector and the use of AI in political decision-making processes can increase the efficiency of public services (Wilson & van der Velden, 2022). However, new governance models are needed to determine whether applications of AI in the public sector comply with social sustainability criteria (Wilson & van der

Velden, 2022). In AI-supported public administration, which risks increasing the complexity of bureaucratic processes, ethical standards need to be clearly defined (Wilson & van der Velden, 2022). AI's potential to transform organizational governance should be supported by smart regulations (Zhao, 2024). Accountable use of AI, especially for corporate boards, can promote sustainable corporate governance practices (Zhao, 2024). From a corporate sustainability perspective, AI offers significant benefits such as reducing carbon footprints, strengthening corporate responsibility policies, and promoting sustainable growth (Tabbakh et al., 2024). However, ethics and transparency principles are of great importance in terms of organizational governance. Corporate boards and the public sector need regulations that increase transparency in the use of AI (Zhao, 2024). AI-based policy-making processes in the public sector can provide a more efficient management model; however, these processes need to be based on ethical standards (Wilson & van der Velden, 2022).

Finally, aligning corporate culture with sustainable AI is a critical factor for a successful transformation in organizational governance. Corporate culture is seen as an element that directly affects the efficiency of sustainable AI policies (Isensee et al., 2021). Adopting sustainable AI principles by organizations is a critical requirement not only for financial sustainability but also for social and environmental sustainability (Isensee et al., 2021).

3.2.2. Social Dimension

Artificial intelligence (AI) has the possibility to provide individuals, communities and organizations with ethical, fair and inclusive access to technology for social sustainability (Rohde et al., 2024). However, the risk of AI deepening social inequalities should not be ignored. Algorithmic biases and ethical issues can lead to discrimination in AI-assisted decision-making, negatively impacting social sustainability (Bolte et al., 2022). One of the biggest social impacts of AI is on education systems. The human-centered AI (HCAI) approach in education makes individual learning processes more effective by providing students with personalized learning experiences (Yang et al., 2021). However, the widespread use of AI in education is changing the roles of teachers and creating the necessity to increase students' digital literacy (Yang et al., 2021). The impact of AI on education systems is directly related to the sustainable development goals (SDGs). AI in education and professional development processes enables individuals to be equipped with the skills required by the digital age, while also raising awareness about ethical AI use (Abulibdeh et al., 2024). However, the widening of the digital divide, i.e. inequalities in access to AI technologies, can jeopardize equal opportunities in education (Yang et al., 2021). Therefore, the use of explainable AI and transparent algorithm designs should be widespread in education systems (Yang et al., 2021). The impact of AI on social sustainability is not limited to education; it also creates significant transformations in areas such as consumer rights and information access. The accuracy of information provided in digital services and products is one of the cornerstones of sustainable AI applications (Kindylidi & Cabral, 2021). However, the use of AI in marketing strategies can also bring risks of misdirection and unethical advertising. Therefore, policies should be created to increase the transparency of AI-supported information systems (Kindylidi & Cabral, 2021). Another critical social dimension is the concept of intergenerational justice. The development of AI policies that will protect the rights of future generations is seen as a critical necessity not only in terms of environmental sustainability but also in terms of social sustainability (Halsband, 2022). The use of AI as a decision support system, especially in climate policies, has the potential to reduce future environmental risks (Halsband, 2022). However, preserving the principles of ethics and transparency in this process is of great importance for the reliability of AI.

The role that AI can play in combating climate change should be carefully considered in terms of social sustainability. While AI has the potential to develop solutions to reduce carbon emissions, ethical regulations and international collaborations are needed for these solutions to be effective (Schütze, 2024).

In conclusion, although the benefits of AI in terms of social sustainability are great, risks such as ethical issues, inequalities and lack of transparency should be considered. AI used in education, consumer rights and climate policies in a fair, inclusive and ethical manner can become an important tool to support social sustainability.

3.2.3. Ecological Dimension

This review explored two main research streams related to Sustainability and Artificial Intelligence. Perspective for Sustainability of AI considers sustainability's social, ecological, and economic aspects. Previously, Rohde et al. (2024) proposed an evaluation framework taking into AI lifecycle account. Thus, according to researchers, developing and establishing AI systems should integrate perspectives that include organizational governance and social, ecological, and economic impacts. Since the study of (Rohde et al., 2024) suggests a comprehensive framework for Sustainable AI, the dimensions and evaluation criteria they offered constitute a solid foundation for this study. In the systematic literature review conducted within the scope of this study, it was determined that a significant amount of the studies examined were related to the Sustainable AI-Ecological dimension. It has been revealed that the sub-themes of Sustainable AI studies focusing on Ecological dimension overlap and are compatible with the framework suggested by (Rohde et al., 2024). 20 of these studies were specifically related to "energy consumption", 15 to "CO_2 and GHG emissions", 9 to "sustainability potential in implementation", and 9 to "embodied and shared resource consumption of hardware infrastructure”. Table 2 represents studies focusing on the associated sub-themes.

Table 2.

Distribution of the Studies Based on Sub-Themes

Sub-Themes	Studies
Energy consumption	(Bolón-Canedo et al., 2024; Budennyy et al., 2022; Dai et al., 2024; Durlik et al., 2024; Escarda et al., 2025; Ferro et al., 2023; Kindylidi & Cabral, 2021; Kopka & Grashof, 2022; Kunkel et al., 2023; Nishant et al., 2020; Ofek & Maimon, 2023; Perucica & Andjelkovic, 2022; Raman et al., 2024; Robbins & van Wynsberghe, 2022; Rohde et al., 2024; Tabbakh et al., 2024; Tandale & Stoffel, 2023; Wang, Li, et al., 2024; Yaghoubi & Kumru, 2024; Yun et al., 2016)
CO_2 and GHG emissions	(Ali et al., 2024; Bolón-Canedo et al., 2024; Budennyy et al., 2022; Durlik et al., 2024; Falk et al., 2024; Kindylidi & Cabral, 2021; Kunkel et al., 2023; Nishant et al., 2020; Ofek & Maimon, 2023; Raman et al., 2024; Robbins & van Wynsberghe, 2022; Rohde et al., 2024; Tabbakh et al., 2024; Wang, Li, et al., 2024; Yaghoubi & Kumru, 2024)
Sustainability potential in implementation	(Bolón-Canedo et al., 2024; Durlik et al., 2024; Falk et al., 2024; Kindylidi & Cabral, 2021; Kunkel et al., 2023; Manzoor et al., 2021; Robbins & van Wynsberghe, 2022; Rohde et al., 2024; Wu & Shang, 2020)
Embodied and shared resource consumption of hardware infrastructure	(Bolón-Canedo et al., 2024; Durlik et al., 2024; Kindylidi & Cabral, 2021; Kunkel et al., 2023; Lewerenz et al., 2024; Pal et al., 2024; Raman et al., 2024; Robbins & van Wynsberghe, 2022; Rohde et al., 2024)

It is explored that the studies classified under this topic can focus on more than one sub-theme. The contents of the studies focused on sub-themes in the Ecology dimension are explained below.

***Energy consumption**:* Studies under this theme mainly concentrated on the energy consumption issues during the AI systems development. Accordingly, model selection, reduction of model complexity, parameter selection, techniques for enhancing model efficiency and training were the main arguments of studies. For instance, Tabbakh et al. (2024) suggested a framework for decreasing AI's environmental footprint and enhancing energy efficiency. Dai et al. (2024) proposed energy-efficient inference models specifically for IoT devices utilising dynamic pruning and frequency scaling.

According to Kopka and Grashof (2022), the sustainability impact of AI is contingent upon regional energy infrastructures and industry priorities. Thus, AI's influence on regional energy consumption in Germany was examined.

CO_2 and GHG emissions: This stream of research concentrated on CO_2 footprint, CO_2 efficiency, and emission issues. For instance, Budennyy et al. (2022) proposed a tool that tracks carbon emissions, increasing awareness and sustainable AI implementations, while Ofek and Maimon (2023) suggested an interdisciplinary framework integrating complex systems theory with ecological considerations. Another study examined green AI as a crucial strategy for improving the environmental sustainability of AI systems. Hence, methodologies for developing energy-efficient machine learning algorithms and models (green-in AI) and instruments for precise measurement and optimisation of energy use were discussed (Bolón-Canedo et al., 2024).

Sustainability potential in implementation: Despite the limited number of papers gathered under this theme, this argument also highlights the areas that future research should prioritise. Rohde et al. (2024) conceptualised the indicators of this dimension as the incorporation of sustainability factors inside decision-making processes, advocacy for sustainable products and sustainable consumption, minimisation of resource use in processes or products, and the effect of the AI system on product quality and longevity. However, those issues have been examined relatively minimally by previous research.

Embodied and shared resource consumption of hardware infrastructure: Studies under this theme mainly considered the efficiency of hardware components, data centers, hardware recycling and reuse rate. This is compatible with the framework of (Rohde et al. 2024).

Lewerenz et al. (2024) suggested a configurable neurone circuit that improves the scalability and sustainability of AI hardware systems, while Pal et al. (2024) developed a green polymer-based memristor, achieving a power consumption reduction.

3.2.4. Economic Dimension

Artificial intelligence (AI) presents significant opportunities and risks in terms of economic sustainability. Today, companies and governments must increase the economic value of AI while also considering its ethical and environmental impacts (Zhao & Gómez Fariñas, 2023). In particular, the integration of AI is increasingly needed to develop corporate social responsibility (CSR) programs, improve resource management, and make decision-making processes more efficient (Zhao & Gómez Fariñas, 2023). However, despite the advantages offered by big data analytics, companies may experience difficulties in decision-making processes due to the density of data. In addition, the lack of regulatory frameworks leads the private sector to determine its own ethical standards, creating problems in terms of accountability and transparency (Kar et al., 2022). AI-supported sustainable economy models offer opportunities such as reducing carbon emissions, adopting a circular economy approach and optimizing resource management (Kar et al., 2022). In particular, Industry 5.0 contributes to the sustainability of value-added production processes by accelerating the integration of human-centered artificial intelligence into economic systems (Martini et al., 2024). However, the misuse of AI carries the risk of increasing economic inequalities. Groups with limited access to technological infrastructure and education Martini et al. (2024) may be excluded from economic growth processes, which may further deepen the income gap (Fernandez-Aller et al., 2021). The economic contributions of AI are becoming evident in different sectors. In the construction and engineering sector, waste management is optimized, and energy consumption is reduced thanks to AI-supported systems (Manzoor et al., 2021). In particular, predictive maintenance applications provide more efficient resource management by reducing costs in infrastructure projects (Manzoor et al., 2021). In the food industry, big data analytics and AI-supported systems offer various advantages such as improving waste management in the supply chain, increasing quality control and optimizing productivity (S. Sharma et al., 2021). The development of economically sustainable AI systems should be supported by solutions that increase the energy efficiency of data centers. New-generation computing systems, such as neuromorphic hardware, significantly reduce the energy consumption of AI applications, allowing for the creation of more environmentally friendly and efficient data centers (Vogginger et al., 2024). However, the energy intensity of AI is a major problem on a global scale. The high energy consumption of data centers poses a serious risk to environmental sustainability, and therefore green technology investments and energy-efficient AI solutions have become a great necessity (Schütze, 2024). In addition, the effects of artificial intelligence on the labour market should also be carefully considered. While increasing automation causes job losses in some sectors, it also creates new business areas and professions (Isensee et al., 2021). At this point, supporting sustainable corporate culture with artificial intelligence can help the workforce adapt to changing economic conditions. It is critical for sustainable economic growth for companies to invest in training and talent development programs that can adapt their employees to new technologies (Isensee et al., 2021).

In conclusion, while AI has great potential for economic sustainability, this potential needs to be managed with ethical, environmental and social impacts in mind. Data center solutions that reduce carbon footprints, sustainable workforce policies and the adoption of circular economy models will enable AI to support economic growth while also ensuring environmental and social sustainability.

4. Discussion and Conclusion

This comprehensive study systematically examines the multifaceted role of artificial intelligence (AI) in the realm of sustainability. It delves into both the contributions AI makes to sustainable development and the inherent sustainability of AI itself. The findings highlight that while AI significantly impacts economic and industrial sustainability, its effects on environmental and social dimensions remain underexplored (Palomares et al., 2021; Sætra, 2021). Moreover, ensuring the sustainability of AI poses critical challenges, predominantly in terms of energy consumption, carbon emissions, and ethical governance (Bolón-Canedo et al., 2024; Rohde et al., 2024). A key observation from the literature is that AI contributes substantially to the accomplishment of Sustainable Development Goals (SDGs), especially in industry, innovation, and infrastructure (SDG 9) as well as economic growth (SDG 8). However, there is a lack of research on AI's role in addressing social issues such as reduction inequalities (SDG 10) and gender equality (SDG 5) (Nasir et al., 2023) .This suggests that AI-driven sustainability efforts should expand beyond economic and industrial applications to incorporate broader social benefits. Instead, the sustainability of AI itself has emerged as an equally critical issue. The environmental footprint of AI, particularly the energy-intensive nature of training deep learning models, has been widely documented (Kopka & Grashof, 2022). AI systems require substantial computational resources, leading to increased carbon emissions and exacerbating sustainability concerns. Studies have suggested solutions such as energy-efficient algorithms, green data centers, and sustainable AI infrastructure to mitigate these negative effects (Lewerenz et al., 2024; Pal et al., 2024). Another crucial aspect of sustainable AI is ethical governance. The literature highlights the necessity for frameworks that ensure AI's transparency, accountability, and fairness. Governance models integrating AI into corporate sustainability strategies have been proposed as a means to align AI-driven growth with ethical considerations (Rohde et al., 2024). Without such measures, there is a risk that AI could perpetuate existing inequalities or lead to unintended socio-economic consequences. While this study systematically reviewed existing literature, several research gaps were identified. First, there is a need for further empirical studies on AI's impact on social sustainability. The current focus on economic benefits should be balanced with research that evaluates AI's role in promoting inclusivity and equitable access to technology. Second, the environmental impact of AI should be studied more comprehensively. Although the literature acknowledges AI's high energy consumption, research on green AI practices and their effectiveness remains limited. Finally, interdisciplinary approaches integrating AI, sustainability, and policy frameworks should be developed to create holistic AI governance strategies.

In conclusion, artificial intelligence (AI) presents both opportunities and challenges in the context of sustainability. While AI has demonstrated significant contributions to economic and industrial sustainability, its social and environmental impacts require greater attention. Additionally, the sustainability of AI itself demands urgent consideration, particularly regarding energy efficiency and ethical governance. Future research should adopt a multidimensional approach, considering AI's long-term implications for environmental, economic, and social sustainability. By addressing these challenges, AI can be harnessed as a dominant tool for achieving sustainable development while ensuring its own sustainability.

5. Funding

This research was not funded by any public, commercial, or not-for-profit funding agency.

6. Conflict of Interest

The authors declare no conflict of interest related to this manuscript.

7. Declaration of Generative Ai and Ai-Assisted Technologies in The Writing Process

During the preparation of this work, the authors utilized ChatGPT to assist with language verification and polishing. Subsequently, the authors reviewed and edited the content as necessary and bear sole responsibility for the content of the publication.

REFERENCES

Abulibdeh, A., Zaidan, E., & Abulibdeh, R. (2024). Navigating the confluence of artificial intelligence and education for sustainable development in the era of industry 4.0: Challenges, opportunities, and ethical dimensions. Journal of Cleaner Production, 437. https://doi.org/10.1016/j.jclepro.2023.140527

Adewale, B. A., Ene, V. O., Ogunbayo, B. F., & Aigbavboa, C. O. (2024). A Systematic Review of the Applications of AI in a Sustainable Building's Lifecycle. In Buildings (Vol. 14, Issue 7). Multidisciplinary Digital Publishing Institute (MDPI). https://doi.org/10.3390/buildings14072137

Ahmad, T., Zhang, D., Huang, C., Zhang, H., Dai, N., Song, Y., & Chen, H. (2021). Artificial intelligence in sustainable energy industry: Status Quo, challenges and opportunities. In Journal of Cleaner Production (Vol. 289). Elsevier Ltd. https://doi.org/10.1016/j.jclepro.2021.125834

Ali, S., Fapi, E. T., Jaumard, B., & Planche, A. (2024). Focus on Carbon Dioxide Footprint of AI/ML Model Training. 524–529. https://doi.org/10.1109/imsa61967.2024.10652803

Alshahrani, R., Yenugula, M., Algethami, H., Alharbi, F., Shubhra Goswami, S., Noorulhasan Naveed, Q., Lasisi, A., Islam, S., Khan, N. A., & Zahmatkesh, S. (2024). Establishing the fuzzy integrated hybrid MCDM framework to identify the key barriers to implementing artificial intelligence-enabled sustainable cloud system in an IT industry. Expert Systems with Applications, 238. https://doi.org/10.1016/j.eswa.2023.121732

Bolón-Canedo, V., Morán-Fernández, L., Cancela, B., & Alonso-Betanzos, A. (2024). A review of green artificial intelligence: Towards a more sustainable future. Neurocomputing, 599. https://doi.org/10.1016/j.neucom.2024.128096

Bolte, L., Vandemeulebroucke, T., & van Wynsberghe, A. (2022). From an Ethics of Carefulness to an Ethics of Desirability: Going Beyond Current Ethics Approaches to Sustainable AI. Sustainability (Switzerland), 14(8). https://doi.org/10.3390/su14084472

Bossert, L. N., & Hagendorff, T. (2023). The ethics of sustainable AI: Why animals (should) matter for a sustainable use of AI. Sustainable Development, 31(5), 3459–3467. https://doi.org/10.1002/sd.2596

Bracarense, N., Bawack, R. E., Wamba, S. F., & Carillo, K. D. A. (2022). Artificial Intelligence and Sustainability: A Bibliometric Analysis and Future Research Directions. Pacific Asia Journal of the Association for Information Systems, 14(2), 136–159. https://doi.org/10.17705/1pais.14209

Budennyy, S. A., Lazarev, V. D., Zakharenko, N. N., Korovin, A. N., Plosskaya, O. A., Dimitrov, D. V., Akhripkin, V. S., Pavlov, I. V., Oseledets, I. V., Barsola, I. S., Egorov, I. V., Kosterina, A. A., & Zhukov, L. E. (2022). eco2AI: Carbon Emissions Tracking of Machine Learning Models as the First Step Towards Sustainable AI. Doklady Mathematics, 106, S118–S128. https://doi.org/10.1134/S1064562422060230

Chen, W., Men, Y., Fuster, N., Osorio, C., & Juan, A. A. (2024). Artificial Intelligence in Logistics Optimization with Sustainable Criteria: A Review. In Sustainability (Switzerland) (Vol. 16, Issue 21). Multidisciplinary Digital Publishing Institute (MDPI). https://doi.org/10.3390/su16219145

Dai, S., Luo, Z., Luo, W., Wang, S., Dai, C., Guo, B., & Zhou, X. (2024). Energy-Efficient Inference with Software-Hardware Co-Design for Sustainable Artificial Intelligence of Things. IEEE Internet of Things Journal. https://doi.org/10.1109/JIOT.2024.3482288

Di Vaio, A., Palladino, R., Hassan, R., & Escobar, O. (2020). Artificial intelligence and business models in the sustainable development goals perspective: A systematic literature review. Journal of Business Research, 121, 283–314. https://doi.org/10.1016/j.jbusres.2020.08.019

Durlik, I., Miller, T., Kostecka, E., Łobodzińska, A., & Kostecki, T. (2024). Harnessing AI for Sustainable Shipping and Green Ports: Challenges and Opportunities. In Applied Sciences (Switzerland) (Vol. 14, Issue 14). Multidisciplinary Digital Publishing Institute (MDPI). https://doi.org/10.3390/app14145994

Elmousalami, H., Elshaboury, N., & Elyamany, A. H. (2024). Green artificial intelligence for cost-duration variance prediction (CDVP) for irrigation canals rehabilitation projects. Expert Systems with Applications, 249. https://doi.org/10.1016/j.eswa.2024.123789

Escarda, M., Eiras-Franco, C., Cancela, B., Guijarro-Berdiñas, B., & Alonso-Betanzos, A. (2025). Performance and sustainability of BERT derivatives in dyadic data. Expert Systems with Applications, 262. https://doi.org/10.1016/j.eswa.2024.125647

Falk, S., van Wynsberghe, A., & Biber-Freudenberger, L. (2024). The attribution problem of a seemingly intangible industry. In Environmental Challenges (Vol. 16). Elsevier B.V. https://doi.org/10.1016/j.envc.2024.101003

Fernandez-Aller, C., De Velasco, A. F., Manjarres, A., Pastor-Escuredo, D., Pickin, S., Criado, J. S., & Ausin, T. (2021). An Inclusive and Sustainable Artificial Intelligence Strategy for Europe Based on Human Rights. IEEE Technology and Society Magazine, 40(1), 46–54. https://doi.org/10.1109/MTS.2021.3056283

Ferro, M., Silva, G. D., de Paula, F. B., Vieira, V., & Schulze, B. (2023). Towards a sustainable artificial intelligence: A case study of energy efficiency in decision tree algorithms. Concurrency and Computation: Practice and Experience, 35(17). https://doi.org/10.1002/cpe.6815

Gill, A. S., & Germann, S. (2022). Conceptual and normative approaches to AI governance for a global digital ecosystem supportive of the UN Sustainable Development Goals (SDGs). AI and Ethics, 2(2), 293–301. https://doi.org/10.1007/s43681-021-00058-z

Gupta, B. B., Gaurav, A., Panigrahi, P. K., & Arya, V. (2023). Analysis of artificial intelligence-based technologies and approaches on sustainable entrepreneurship. Technological Forecasting and Social Change, 186. https://doi.org/10.1016/j.techfore.2022.122152

Halsband, A. (2022). Sustainable AI and Intergenerational Justice. Sustainability (Switzerland), 14(7). https://doi.org/10.3390/su14073922

Isensee, C., Griese, K.-M., & Teuteberg, F. (2021). Sustainable artificial intelligence: A corporate culture perspective. Sustainability Management Forum | NachhaltigkeitsManagementForum, 29(3–4), 217–230. https://doi.org/10.1007/s00550-021-00524-6

Kar, A. K., Choudhary, S. K., & Singh, V. K. (2022). How can artificial intelligence impact sustainability: A systematic literature review. In Journal of Cleaner Production (Vol. 376). Elsevier Ltd. https://doi.org/10.1016/j.jclepro.2022.134120

Kindylidi, I., & Cabral, T. S. (2021). Sustainability of ai: The case of provision of information to consumers. Sustainability (Switzerland), 13(21). https://doi.org/10.3390/su132112064

Kopka, A., & Grashof, N. (2022). Artificial intelligence: Catalyst or barrier on the path to sustainability? Technological Forecasting and Social Change, 175. https://doi.org/10.1016/j.techfore.2021.121318

Kulkov, I., Kulkova, J., Rohrbeck, R., Menvielle, L., Kaartemo, V., & Makkonen, H. (2024). Artificial intelligence - driven sustainable development: Examining organizational, technical, and processing approaches to achieving global goals. Sustainable Development, 32(3), 2253–2267. https://doi.org/10.1002/sd.2773

Kunkel, S., Schmelzle, F., Niehoff, S., & Beier, G. (2023). More sustainable artificial intelligence systems through stakeholder involvement? In GAIA - Ecological Perspectives for Science and Society (Vol. 32, pp. 64–70). Oekom Verlag. https://doi.org/10.14512/gaia.32.S1.10

Lewerenz, M., Passerini, E., Weber, L., Fischer, M., Jimenez Olalla, N., Gisler, R., Emboras, A., Luisier, M., Csontos, M., Koch, U., & Leuthold, J. (2024). A Three-Terminal Memristive Artificial Neuron with Tunable Firing Probability. Advanced Electronic Materials. https://doi.org/10.1002/aelm.202400432

Linaza, M. T., Posada, J., Bund, J., Eisert, P., Quartulli, M., Döllner, J., Pagani, A., Olaizola, I. G., Barriguinha, A., Moysiadis, T., & Lucat, L. (2021). Data-driven artificial intelligence applications for sustainable precision agriculture. Agronomy, 11(6). https://doi.org/10.3390/agronomy11061227

Manzoor, B., Othman, I., Durdyev, S., Ismail, S., & Wahab, M. H. (2021). Influence of artificial intelligence in civil engineering toward sustainable development—a systematic literature review. In Applied System Innovation (Vol. 4, Issue 3). MDPI AG. https://doi.org/10.3390/asi4030052

Martini, B., Bellisario, D., & Coletti, P. (2024). Human-Centered and Sustainable Artificial Intelligence in Industry 5.0: Challenges and Perspectives. Sustainability (Switzerland) , 16(13). https://doi.org/10.3390/su16135448

Marvin, H. J. P., Bouzembrak, Y., van der Fels-Klerx, H. J., Kempenaar, C., Veerkamp, R., Chauhan, A., Stroosnijder, S., Top, J., Simsek-Senel, G., Vrolijk, H., Knibbe, W. J., Zhang, L., Boom, R., & Tekinerdogan, B. (2022). Digitalisation and Artificial Intelligence for sustainable food systems. In

Trends in Food Science and Technology (Vol. 120, pp. 344–348). Elsevier Ltd. https://doi.org/10.1016/j.tifs.2022.01.020

Mushtaq, M. A., Ahmed, H. G. M. D., & Zeng, Y. (2024). Applications of Artificial Intelligence in Wheat Breeding for Sustainable Food Security. In Sustainability (Switzerland) (Vol. 16, Issue 13). Multidisciplinary Digital Publishing Institute (MDPI). https://doi.org/10.3390/su16135688

Nasir, O., Javed, R. T., Gupta, S., Vinuesa, R., & Qadir, J. (2023). Artificial intelligence and sustainable development goals nexus via four vantage points. Technology in Society, 72. https://doi.org/10.1016/j.techsoc.2022.102171

Nie, J., Wang, Y., Li, Y., & Chao, X. (2022). Artificial intelligence and digital twins in sustainable agriculture and forestry: a survey. In Turkish Journal of Agriculture and Forestry (Vol. 46, Issue 5, pp. 642–661). Turkiye Klinikleri. https://doi.org/10.55730/1300-011X.3033

Nishant, R., Kennedy, M., & Corbett, J. (2020). Artificial intelligence for sustainability: Challenges, opportunities, and a research agenda. International Journal of Information Management, 53. https://doi.org/10.1016/j.ijinfomgt.2020.102104

Ofek, N., & Maimon, O. (2023). Beyond Metrics: Navigating AI through Sustainable Paradigms. Sustainability (Switzerland), 15(24). https://doi.org/10.3390/su152416789

Pal, P., Li, H., Al-Ajeil, R., Mohammed, A. K., Rezk, A., Melinte, G., Nayfeh, A., Shetty, D., & El-Atab, N. (2024). Energy Efficient Memristor Based on Green-Synthesized 2D Carbonyl-Decorated Organic Polymer and Application in Image Denoising and Edge Detection: Toward Sustainable AI. Advanced Science. https://doi.org/10.1002/advs.202408648

Palmini, O., & Cugurullo, F. (2024). Design culture for Sustainable urban artificial intelligence: Bruno Latour and the search for a different AI urbanism. Ethics and Information Technology, 26(1). https://doi.org/10.1007/s10676-024-09752-y

Palomares, I., Martínez-Cámara, E., Montes, R., García-Moral, P., Chiachio, M., Chiachio, J., Alonso, S., Melero, F. J., Molina, D., Fernández, B., Moral, C., Marchena, R., de Vargas, J. P., & Herrera, F. (2021). A panoramic view and swot analysis of artificial intelligence for achieving the sustainable development goals by 2030: progress and prospects. Applied Intelligence, 51(9), 6497–6527. https://doi.org/10.1007/s10489-021-02264-y

Paneru, B., Paneru, B., Sapkota, S. C., & Poudyal, R. (2024). Enhancing healthcare with AI: Sustainable AI and IoT-Powered ecosystem for patient aid and interpretability analysis using SHAP. Measurement: Sensors, 36. https://doi.org/10.1016/j.measen.2024.101305

Perucica, N., & Andjelkovic, K. (2022). Is the future of AI sustainable? A case study of the European Union. Transforming Government: People, Process and Policy, 16(3), 347–358. https://doi.org/10.1108/TG-06-2021-0106

Raman, R., Pattnaik, D., Lathabai, H. H., Kumar, C., Govindan, K., & Nedungadi, P. (2024). Green and sustainable AI research: an integrated thematic and topic modeling analysis. Journal of Big Data, 11(1). https://doi.org/10.1186/s40537-024-00920-x

Robbins, S., & van Wynsberghe, A. (2022). Our New Artificial Intelligence Infrastructure: Becoming Locked into an Unsustainable Future. Sustainability (Switzerland), 14(8). https://doi.org/10.3390/su14084829

Rohde, F., Wagner, J., Meyer, A., Reinhard, P., Voss, M., Petschow, U., & Mollen, A. (2024). Broadening the perspective for sustainable artificial intelligence: sustainability criteria and indicators for Artificial Intelligence systems. In Current Opinion in Environmental Sustainability (Vol. 66). Elsevier B.V. https://doi.org/10.1016/j.cosust.2023.101411

Sætra, H. S. (2021). Ai in context and the sustainable development goals: Factoring in the unsustainability of the sociotechnical system. Sustainability (Switzerland), 13(4), 1–19. https://doi.org/10.3390/su13041738

Saheb, T., Dehghani, M., & Saheb, T. (2022). Artificial intelligence for sustainable energy: A contextual topic modeling and content analysis. Sustainable Computing: Informatics and Systems, 35. https://doi.org/10.1016/j.suscom.2022.100699

Schoormann, T., Strobel, G., Petrik, D., Möller, F., & Zschech, P. (2023). Artificial Intelligence for Sustainability—A Systematic Review of Information Systems Literature. In Communications of the Association for Information Systems (Vol. 52, pp. 556–592). Association for Information Systems. https://doi.org/10.17705/1cais.05209

Schütze, P. (2024). The impacts of AI futurism: an unfiltered look at AI's true effects on the climate crisis. Ethics and Information Technology, 26(2). https://doi.org/10.1007/s10676-024-09758-6

Sen, S., Gonzalez, V., Husom, E. J., Tverdal, S., Tokas, S., & Tjøsvoll, S. O. (2024). ERG-AI: enhancing occupational ergonomics with uncertainty-aware ML and LLM feedback. Applied Intelligence. https://doi.org/10.1007/s10489-024-05796-1

Seo, C., Yoo, D., & Lee, Y. (2024). Empowering Sustainable Industrial and Service Systems through AI-Enhanced Cloud Resource Optimization. Sustainability (Switzerland), 16(12). https://doi.org/10.3390/su16125095

Shang, Y., Yang, Q., Pu, Y., & Taghizadeh-Hesary, F. (2024). Employing artificial intelligence and enhancing resource efficiency to achieve carbon neutrality. Resources Policy, 88. https://doi.org/10.1016/j.resourpol.2023.104510

Sharma, A., Podoplelova, E., Shapovalov, G., Tselykh, A., & Tselykh, A. (2021). Sustainable smart cities: Convergence of artificial intelligence and blockchain. Sustainability (Switzerland), 13(23). https://doi.org/10.3390/su132313076

Sharma, S., Gahlawat, V. K., Rahul, K., Mor, R. S., & Malik, M. (2021). Sustainable Innovations in the Food Industry through Artificial Intelligence and Big Data Analytics. In Logistics (Vol. 5, Issue 4). MDPI. https://doi.org/10.3390/logistics5040066

Sipola, J., Saunila, M., & Ukko, J. (2023). Adopting artificial intelligence in sustainable business. Journal of Cleaner Production, 426. https://doi.org/10.1016/j.jclepro.2023.139197

Steingard, D., Balduccini, M., & Sinha, A. (2023). Applying AI for social good: Aligning academic journal ratings with the United Nations Sustainable Development Goals (SDGs). AI and Society, 38(2), 613–629. https://doi.org/10.1007/s00146-022-01459-2

Strielkowski, W., Grebennikova, V., Lisovskiy, A., Rakhimova, G., & Vasileva, T. (2024). AI-driven adaptive learning for sustainable educational transformation. In Sustainable Development. John Wiley and Sons Ltd. https://doi.org/10.1002/sd.3221

Tabbakh, A., Al Amin, L., Islam, M., Mahmud, G. M. I., Chowdhury, I. K., & Mukta, M. S. H. (2024). Towards sustainable AI: a comprehensive framework for Green AI. Discover Sustainability, 5(1). https://doi.org/10.1007/s43621-024-00641-4

Tandale, S. B., & Stoffel, M. (2023). Spiking recurrent neural networks for neuromorphic computing in nonlinear structural mechanics. Computer Methods in Applied Mechanics and Engineering, 412. https://doi.org/10.1016/j.cma.2023.116095

Truby, J. (2020). Governing Artificial Intelligence to benefit the UN Sustainable Development Goals. Sustainable Development, 28(4), 946–959. https://doi.org/10.1002/sd.2048

Ueda, D., Walston, S. L., Fujita, S., Fushimi, Y., Tsuboyama, T., Kamagata, K., Yamada, A., Yanagawa, M., Ito, R., Fujima, N., Kawamura, M., Nakaura, T., Matsui, Y., Tatsugami, F., Fujioka, T., Nozaki, T., Hirata, K., & Naganawa, S. (2024). Climate change and artificial intelligence in healthcare: Review and recommendations towards a sustainable future. In Diagnostic and Interventional Imaging. Elsevier Masson s.r.l. https://doi.org/10.1016/j.diii.2024.06.002

Vogginger, B., Rostami, A., Jain, V., Arfa, S., Hantsch, A., Kappel, D., Schäfer, M., Faltings, U., Gonzalez, H. A., Liu, C., Mayr, C., & Maaß, W. (2024). Neuromorphic hardware for sustainable AI data centers. http://arxiv.org/abs/2402.02521

Walk, J., Kühl, N., Saidani, M., & Schatte, J. (2023). Artificial intelligence for sustainability: Facilitating sustainable smart product-service systems with computer vision. Journal of Cleaner Production, 402. https://doi.org/10.1016/j.jclepro.2023.136748

Wang, Q., Li, Y., & Li, R. (2024). Ecological footprints, carbon emissions, and energy transitions: the impact of artificial intelligence (AI). Humanities and Social Sciences Communications, 11(1). https://doi.org/10.1057/s41599-024-03520-5

Wang, Q., Zhang, F., & Li, R. (2024). Artificial intelligence and sustainable development during urbanization: Perspectives on AI R&D innovation, AI infrastructure, and AI market advantage. Sustainable Development. https://doi.org/10.1002/sd.3150

Wilson, C., & van der Velden, M. (2022). Sustainable AI: An integrated model to guide public sector decision-making. Technology in Society, 68. https://doi.org/10.1016/j.techsoc.2022.101926

Wu, J., & Shang, S. (2020). Managing uncertainty in ai-enabled decision making and achieving sustainability. Sustainability (Switzerland), 12(21), 1–17. https://doi.org/10.3390/su12218758

Yaghoubi, V., & Kumru, B. (2024). Retrosynthetic Life Cycle Assessment: A Short Perspective on the Sustainability of Integrating Thermoplastics and Artificial Intelligence Into Composite Systems. Advanced Sustainable Systems, 8(5). https://doi.org/10.1002/adsu.202300543

Yang, S. J. H., Ogata, H., Matsui, T., & Chen, N. S. (2021). Human-centered artificial intelligence in education: Seeing the invisible through the visible. Computers and Education: Artificial Intelligence, 2. https://doi.org/10.1016/j.caeai.2021.100008

Yigitcanlar, T., & Cugurullo, F. (2020). The sustainability of artificial intelligence: an urbanistic viewpoint from the lens of smart and sustainable cities. Sustainability (Switzerland), 12(20), 1–24. https://doi.org/10.3390/su12208548

Yigitcanlar, T., Mehmood, R., & Corchado, J. M. (2021). Green artificial intelligence: towards an efficient, sustainable and equitable technology for smart cities and futures. Sustainability (Switzerland), 13(16). https://doi.org/10.3390/su13168952

Yun, J. H. J., Lee, D., Ahn, H., Park, K., & Yigitcanlar, T. (2016). Not deep learning but autonomous learning of open innovation for sustainable artificial intelligence. Sustainability (Switzerland), 8(8). https://doi.org/10.3390/su8080797

Zhao, J. (2024). Promoting more accountable AI in the boardroom through smart regulation. Computer Law and Security Review, 52. https://doi.org/10.1016/j.clsr.2024.105939

Zhao, J., & Gómez Fariñas, B. (2023). Artificial Intelligence and Sustainable Decisions. European Business Organization Law Review, 24(1), 1–39. https://doi.org/10.1007/s40804-022-00262-2

Paper #55

Title: Optimizing Large Language Models using Retrieval Augmented Generation and Automated Evaluation

Author(s): Ömer Kartlı, Selim Akyokuş and Salih Sarp

Abstract:
This paper explores how Retrieval-Augmented Generation (RAG) and automated evaluation using RAGAS can improve the performance and assessment of large language models. By combining vector search and reference-free scoring, the authors demonstrate increased accuracy, cost-efficiency, and contextual quality in both open-source and commercial models.

Keywords: LLMs, RAG, RAGAS, Generative AI, Evaluation Metrics, NLP

Optimizing Large Language Models using Retrieval Augmented Generation and Automated Evaluation

Professor Dr. Selim Akyokuş, Lecturer, İstanbul, Türkiye
Assist. Prof. Salih SARP, Lecturer, Kocaeli, Türkiye
Ömer KARTLI M. S. Istanbul, Turkiye
Hisar Health Research Center, Istanbul, Turkiye
Computer Engineering M. S., Istanbul Medipol University, Istanbul, Turkiye
omer.kartli@std.medipol.edu.tr

***Özetçe*— Bu projede, büyük dil modellerinin (LLM) performansını artırmak amacıyla Bilgi Getirili Üretimin (RAG) yöntemleri entegre edilerek, modellerin doğruluk, alan özgüllüğü ve bağlam farkındalığının geliştirilmesi hedeflenmektedir. Projede, RAG ile entegre edilmiş LLM'ler üzerinden otomatik değerlendirme yapabilmek için Bilgi Getirili Üretimin Otomatik Değerlendirilmesi (RAGAS) sistemi kullanılacaktır. Ayrıca, açık kaynaklı (örneğin LLaMA, Falcon) ve ticari (örneğin GPT-4, Claude) modellerin, çeşitli ve çok yönlü veri setleri üzerinde gerçekleştirecekleri deneysel çalışmalarla kapsamlı bir karşılaştırmalı analiz sunulacaktır. Bu analizde, modellerin doğruluk, yanıt hızı, maliyet etkinliği gibi performans metrikleri değerlendirilecek, grafik ve tablolar aracılığıyla sonuçlar görselleştirilecektir. Proje, elde edilecek bulgularla hem araştırmacılara hem de endüstri uygulayıcılarına, LLM'lerin RAG ile optimize edilmiş versiyonlarının pratik kullanımına yönelik somut öneriler ve stratejiler sağlamayı amaçlamaktadır.**

Anahtar Kelimeler — Büyük Dil Modelleri (LLMs), Bilgi Getirili Üretim (RAG), Bilgi Getirili Üretimin Otomatik Değerlendirilmesi (RAGAS), Doğal Dil İşleme (NLP).

***Abstract*— In this project, we aim to enhance the performance of large language models (LLMs) by integrating Retrieval-Augmented Generation (RAG) methods. This integration is intended to improve the models' accuracy, domain specificity, and contextual awareness. To automatically evaluate LLMs that incorporate RAG, the Retrieval-Augmented Generation Automated Scoring (RAGAS) system will be utilized. Furthermore, a comprehensive comparative analysis will be conducted through experimental studies on diverse and versatile datasets, comparing open-source models (e.g., LLaMA, Falcon) with commercial models (e.g., GPT-4, Claude). This analysis will evaluate performance metrics such as accuracy, response speed, and cost-effectiveness, with the results visualized using graphs and tables. The project aims to provide concrete recommendations and strategies for the practical application of RAG-optimized LLMs, offering valuable insights to both researchers and industry practitioners.**

Keywords — Large Language Models (LLMs), Retrieval Augmented Generation (RAG), Automated Evaluation of Retrieval Augmented Generation (RAGAS), Natural Language Processing (NLP).

I. INTRODUCTION

The emergence of large language models (LLMs) has revolutionized natural language processing (NLP) tasks, leading to significant advances in areas such as question-answering, summarization, and conversational agents. However, LLMs still face challenges such as hallucinations, limited domain knowledge, and difficulties in evaluating generated outputs. Retrieval-Augmented Generation (RAG) offers a promising solution by integrating external information retrieval mechanisms into the generation process. Moreover, automated evaluation frameworks like RAGAS provide systematic methods to assess the performance of RAG systems without relying on human evaluations.

RAG systems enhance LLM performance by using external knowledge bases to supply relevant context, thereby improving the accuracy and relevance of the generated responses. The modular design of RAG allows for the interchangeability of components such as the base language model and retrieval mechanisms, offering flexibility in optimizing model performance for specific tasks and domains [1].

RAGAS (Retrieval-Augmented Generation Assessment) provides a reference-free evaluation framework for RAG pipelines. It assesses various dimensions of RAG systems—such as the quality of retrieval, the LLM's fidelity in using the retrieved content, and the overall quality of the output—without the need for reference annotations of actual responses, making it a valuable tool for the rapid development and deployment of LLMs [2].

Studies comparing RAG with traditional fine-tuning methods have demonstrated that, particularly in scenarios involving less common or domain-specific knowledge, RAG outperforms fine-tuning. While fine-tuning requires significant computational resources and extensive data preparation, RAG offers a more scalable and efficient alternative by dynamically retrieving relevant information during inference [3].

The evaluation of the retrieval component is critical in RAG systems, as the relevance and quality of the retrieved documents directly impact the final output. Novel evaluation approaches—such as eRAG—assess the effect of each retrieved document on the generated response, allowing a more detailed understanding of retrieval quality and its impact on overall system performance [4].

LLMs enhanced with RAG have shown significant potential in various application areas such as healthcare, legal services, customer support, and language learning tools. These models not only improve the accuracy and relevance of responses but also reduce the risk of hallucinations, making them suitable for applications where reliability is critical [5].

The integration of Retrieval-Augmented Generation with large language models significantly advances natural language processing by addressing the inherent limitations of traditional LLMs. Automated evaluation frameworks like RAGAS streamline the development and assessment process, contributing to the creation of more robust and reliable AI applications. Comparative studies, especially in environments with limited resources or those requiring domain-specific knowledge, emphasize the advantages of RAG over fine-tuning. The continuous evolution of RAG methods and evaluation techniques promises further enhancements in the capabilities and applicability of LLMs across various domains.

II. RELATED WORK

The fundamental principles and applications of the Retrieval-Augmented Generation (RAG) approach are comprehensively discussed in a survey by Wu et al. [1]. This study details the building blocks of RAG systems—retrieval (retriever), information integration (fusion), and generation (generator)—and focuses on how LLMs can reduce hallucination problems and incorporate up-to-date information. Wu et al. systematically compare various retriever and fusion techniques and discuss which components can be optimized according to different application scenarios, demonstrating the wide-ranging applicability of RAG.

The RAGAS framework, developed by Es et al. [2], is an automated evaluation approach designed for RAG systems. RAGAS develops metrics that measure the relevance of retrieved information, the fidelity with which an LLM uses that information, and the overall quality of the generated response—all without needing reference annotations. This approach is especially advantageous for models accessed via closed APIs, offering an alternative to traditional evaluation methods that depend on inaccessible model probability values. Additionally, the metrics provided by RAGAS allow for separate analysis of the performance of different system modules, facilitating better identification of error sources.

Another significant study by Soudani et al. [3] compares fine-tuning with RAG-based approaches. Their work shows that in scenarios involving less common or domain-specific information, traditional fine-tuning requires high computational resources and extensive data preparation, whereas RAG's dynamic retrieval of relevant information can achieve similar performance gains at a lower cost. The experimental results highlight RAG's advantages in scalability and efficiency and offer guidance on the preferred method based on the application context.

Salemi and Zamani emphasize the critical importance of the retrieval module (retriever) in RAG systems [4]. Their study experimentally demonstrates that the quality and relevance of retrieved documents directly affect the accuracy of the LLM's responses. In particular, accurate and focused retrieval plays a decisive role in overall system performance, and the paper provides detailed analyses of various retriever methods and similarity metrics.

Finally, a user study conducted by Tyen et al. [5] offers important insights into the effective use of RAG methods in real-world applications, such as chatbots. This study shows that LLM-based chatbots, enhanced by external information integration, are effective in improving users' language practice and interaction skills. User feedback and experimental results support the potential of RAG to enhance user experience.

The common thread among these studies is that they demonstrate the RAG approach as a vital tool for mitigating LLMs' inherent limitations and enhancing system performance by integrating up-to-date and reliable information. Each study, through its own methods and experimental analyses, sheds light on different aspects of RAG (e.g., retriever quality, fusion strategies, automated evaluation metrics) and provides findings that guide future research. This collective work enables the development of both theoretical and experimental strategies for more effective deployment of RAG-based systems in practical applications.

III. METHODOOGICAL APPROACH

This section details the methodology employed in the project. The performance of large language models (LLMs) was enhanced by integrating the Retrieval-Augmented Generation (RAG) approach along with an automated evaluation framework (RAGAS). An experimental setup was implemented across various datasets to conduct a comprehensive comparative analysis between open-source and commercial models.

A. Retrieval-Augmented Generation (RAG) Integration

The primary objective is to overcome LLMs' limitations—such as internal knowledge gaps, hallucinations, and lack of domain specificity—by integrating the RAG method. In this approach, documents dynamically retrieved from external knowledge bases are provided as additional context to the base language model (e.g., LLaMA, Falcon, GPT-4, Claude).

Data Preprocessing and Vector Representation: Raw text data compiled from various sources is first cleaned, segmented, and chunked to ensure its suitability. Each text fragment is then transformed into a vector representation using LLM-based encoders (e.g., text-embedding-ada-002). These vector representations are stored in a vector database optimized for ANN (Approximate Nearest Neighbor) search algorithms, enabling fast and effective query responses [1].

Information Retrieval: For each user query, the most relevant pieces of information are dynamically retrieved using ANN search algorithms operating on the generated vector representations. This modular design allows the retrieved context to be appended to the base language model, ensuring that up-to-date and domain-specific information is effectively incorporated into the response generation process.

B. Automated Evaluation: The RAGAS Framework

To assess the accuracy, fidelity, and relevance of the generated responses, the RAGAS (Retrieval-Augmented Generation Automated Scoring) system is used. Notably, RAGAS does not require reference response annotations.

Evaluation Metrics:
RAGAS automatically measures three key quality dimensions:

- Faithfulness: The extent to which the generated response reflects the information in the retrieved context.
- Answer Relevance: The degree to which the response aligns with the information required by the query.
- Context Relevance: The appropriateness and focus of the retrieved information with respect to the query.

Implementation: Rather than relying on probability values from LLMs, RAGAS evaluates responses using automatically generated text-based scoring and statistical analysis methods. This approach allows for the performance of models—even those with closed APIs—to be analyzed using reference-free evaluation strategies.

C. Experimental Setup and Dataset Preparation

Dataset Preparation: Datasets tailored to various application domains are processed through cleaning, segmentation, and chunking operations while considering domain specificity and information diversity. For each document, vector representations are created and integrated into an ANN-based vector database [1].

Experimental Setup: Responses generated by different LLMs (both open-source and commercial) after appending the retrieved context are evaluated using RAGAS metrics. Experiments are conducted to assess performance in terms of response accuracy, response time, computational cost, and scalability [3][4].

D. Performance Metrics and Comparative Analysis

Within the project, the performance of LLMs after RAG integration is evaluated using the following metrics:

- Response Accuracy: Measured using RAGAS metrics, this quantifies the alignment of the generated response with the information required by the query.
- Response Time: The time taken to respond to a query is analyzed to assess system efficiency.
- Computational Cost: A comparison is made of the computational resources and processing times across different LLMs.
- Scalability: The system's performance is examined as the size and diversity of the dataset increase. These analyses are visualized and interpreted using graphs and tables [3][4][5].

E. Implementation Steps

The overall methodological steps followed in the project can be summarized as follows:

1. Data Preprocessing: Clean the raw text data and perform segmentation and chunking.
2. Vector Representation Creation: Convert each text fragment into a vector representation using an LLM-based encoder and integrate it into a database for ANN search.
3. Information Retrieval: Dynamically retrieve the most relevant pieces of information for user queries from the vector database using ANN search algorithms.
4. Response Generation: Generate context-supported responses by appending the retrieved information to the base language model.
5. Automated Evaluation: Automatically score the generated responses by measuring their fidelity, answer relevance, and context relevance using the RAGAS framework.
6. Comparative Analysis: Compare the performance of different LLMs in terms of response accuracy, response time, computational cost, and scalability using statistical and visual tools.

This methodology not only enables LLMs to effectively incorporate up-to-date and domain-specific information through external knowledge integration but also allows for reference-free measurement of system performance via automated evaluation.

A. Equations

For each qi, we calculate the similarity sim(q, qi) to the original question q as the cosine between the corresponding embeddings. The answer relevance score, AR, for question q is then calculated as:

$$AR = \frac{1}{n}\sum_{i=1}^{n} sim(q, qi) \qquad (1)$$

In here:

- q represents the question,
- qi represents the candidate questions derived from the given answer,
- sim(q,qi) represents the cosine similarity between q and qi,
- n represents the number of candidate questions generated.

The context relevance score is then calculated as follows:

$$CR = \frac{Çıkarılan\ Cümle\ Sayısı}{c(q)\ içindeki\ toplma\ cümle\ sayısı}$$

In here:

- c(q) indicates the context brought to the question,
- "Number of extracted sentences" indicates the number of sentences that can help the question from the context,
- "Total number of sentences" indicates all sentences in c(q).

Finally, the loyalty score, VE, is then calculated as:

$$F = \frac{|V|}{|S|}$$

In here:

- |S| is the total number of short and focused statements extracted from the answer,
- |V| is the number of these statements supported by the context.

IV. L Performance Comparison of LLM Models

In the experiments, the performances of Llama 3.1, Llama 3.2, Llama-3-Groq-Tool-Use and Gemini Flash models were comprehensively compared in terms of accuracy, response time, cost-effectiveness and context awareness. All models were evaluated in a Knowledge-Generated Generation (RAG) scheme, supported by context obtained from an external information source. In the evaluation of the responses, automatic metrics were obtained using the Retrieval-Augmented Generation Automated Scoring (RAGAS) system. In the following sections, the results obtained for each metric are presented graphically and in tables, and the differences between the models are analyzed.

Table 1. Performance metrics of the experimentally compared LLM models. (Accuracy and Context Score are scores between 0-100; Response Time is the average time for a question, and Cost is the approximate cost per 1000 output tokens.)

TABLE 1. Performance metrics of LLM models.

Model	*Accuracy*	Response Time	Cost ($/1k Token)	*Context Awareness*
Llama 3.1	80	4.0 s	0.0012	85
Llama 3.2	85	3.5 s	0.0012	90
Llama-3-Groq -Tool-Use (70B)	88	1.0 s	0.0008	92
Gemini Flash	90	1.2 s	0.0005	95

The table above provides a general summary of the tests performed. Now let's look at each performance metric individually.

Accuracy

The experimental results show that the Gemini Flash model has the highest accuracy. This model was able to answer questions correctly with approximately 90% accuracy on different datasets. The Llama-3-Groq-Tool-Use model also showed a similarly high accuracy, achieving around 88% success. Since this model is fine-tuned for special skills such as tool use and function invocation, it showed strong performance even on complex tasks. The Llama 3.2 model, the developed version of the open-source Llama series, ranked third with approximately 85% accuracy, while the Llama 3.1 model fell slightly behind with an accuracy of around 80% (Table 1). These results reveal that the difference between the most advanced closed model and open-source models is at the level of 5-10%. In fact, it has been reported in the literature that the highest-level commercial models such as GPT-4 provide ~88-89% accuracy in multi-task language understanding benchmarks, while the best open models remain around ~84%. In our experiments, Gemini Flash (Google's latest model) achieved the highest level of accuracy, reaching the performance that implicit models can reach.

As a result of the RAG integration, all models exhibited significantly higher accuracy compared to their pure counterparts. Providing the model with relevant document fragments from an external information source ensured that the answers were based on up-to-date and accurate information. In this way, the hallucination rate of the models decreased, and the probability of reaching the correct answer appropriate to the question increased. Indeed, it is known that the RAG technique provides access to up-to-date information by exceeding the information recall limits of LLMs and reduces the risk of hallucination. In our automatic evaluation, the reference-free accuracy scores of models using RAG were also high. In particular, the "Response Relevance" metric (relevance to the information required by the question) measured by RAGAS was ~0.90 on average for Gemini Flash and ~0.88 for Llama-3-Groq. This metric is an indicator of how accurately the model answers focus on the question. Similarly, the fidelity scores were higher for large models, indicating that the answers were faithful to the given source.

In general, models with large parameters and well-tuned models came out on top in the accuracy metric, as expected. However, Llama variants run with open and cost-effective methods were also able to show a performance that came very close to closed models. Accuracy rates of up to 90% prove that these systems can produce reliable answers when fed with the right context.

Context Awareness

Context awareness is a concept that expresses how well models can use additional pieces of information and previous interactions. In this study, we evaluated context awareness specifically through the RAG scenario: The models produced a response to the query along with relevant document pieces dynamically pulled from a vector database. Therefore, the "context" here is the external pieces of information related to the user's question. In the evaluation, we focused on the model's success in integrating this context into the answer, and on the model's ability to work within a wide context window.

Experiments have shown that the answers of all models supported by RAG have become highly sensitive to context. The most concrete indicator of this is the high level of "Context Relevance" scores measured by RAGAS for all models. This metric evaluates whether the context passages extracted are really focused on the question. The average context relevance scores for all queries were measured above 0.95 (values under the heading Context Score in Table 1). This shows that the information retrieval module works quite accurately for each model, and that the text pieces presented to the models are largely relevant. In the experimental setup, since the most appropriate few passages for each question are selected according to vector similarity and given to the model, the quality of the context is the same in all models. In this respect, the main differentiating factor in the context awareness assessment is the degree to which the models use this provided information faithfully.

The "Faithfulness" metric of the RAGAS framework scores the extent to which the model response reflects the given context information. This metric is, in a sense, a critical indicator of context awareness. In our experiment, we observed that stronger models have higher fidelity scores. For example, Gemini Flash almost always correctly reflected the critical information elements in the provided context in its response, and its RAGAS fidelity score was measured as ~0.93. Similarly, the Llama-3-Groq model scored ~0.90. While the fidelity score of the Llama 3.2 model was ~0.87, this decreases to ~0.85 in the Llama 3.1 model (average values). Although these differences are small, they indicate that more highly trained or larger models have some advantage in utilizing context. It can be said that larger models can better assimilate the given text and transfer it to the answer thanks to their language understanding capacity.

On the other hand, an interesting finding was that the strongest model, Gemini Flash, rarely tended to add out-of-context information. Sometimes the model tried to add additional details that it had learned during its training but were not explicitly included in the context text. This did not affect the accuracy of the answer, but it did cause a small decrease in the RAGAS fidelity metric. For example, in one question, the Gemini model included the relevant date in its answer based on its own knowledge, even though no date information was given in the context. Even if the answer was correct, RAGAS did not find this information in the context, thus slightly decreasing the score in terms of fidelity. In contrast, the smaller Llama models preferred to rely solely on the given text rather than making up parts they did not know, sometimes at the cost of leaving the answer incomplete. This kept their context fidelity relatively high. This observation suggests that the extensive world knowledge of large models can sometimes be a disadvantage, as they may overconfidently try to supplement external information. When using RAG, the ideal is for the model to produce an answer only from the given documents. Therefore, when necessary, it was useful to give instructions to the model to respond only from the context when prompted.

Contribution of RAGAS and Automated Assessment

In this study, the RAGAS (Retrieval-Augmented Generation Automated Scoring) framework was used to minimize the need for human assessment and to obtain rapid feedback. RAGAS offers metrics specifically developed to measure the performance of a RAG system, and does not require any reference correct answer. It automatically scores the quality of model outputs, their relevance to the given context, and their suitability to the question. In the literature, it is emphasized that automated assessment tools such as RAGAS provide a systematic way to measure the performance of RAG systems without the need for human peer-reviewed evaluations. These metrics produce values between 0 and 1 for the suitability of the model answer to the question, the suitability of the presented context to the question, and the fidelity of the answer to the context content, respectively. RAGAS assigns these scores using statistical methods by examining the LLM output and the context used. For example, the fidelity metric measures how much the answer is based on context by evaluating the similarity of the expressions in the model answer to the sentences in the context. The response relevance metric indirectly tests the suitability of the given answer to the original question by asking the model "candidate questions" derived from the answer instead of the question. These methods allow the assessment of the suitability and reliability of the answer to the task without the need for an explicit golden answer. During the development of RAGAS, Es et al.'s work showed that these metrics closely parallel human judgments: two human raters scored 95% of the time on fidelity and context relevance scores, and 90% of the time on response relevance scores. This high correlation indicates that RAGAS is a reliable assessment tool.

In our experiments, the use of RAGAS was key to quantifying the differences in model performance. We calculated RAGAS metrics for each question answer for each model separately, resulting in a large automated assessment table for our test set of hundreds of questions. This table allowed us to analyze the strengths and weaknesses of the models in multiple dimensions. For example, we noticed that the Llama 3.1 model scored significantly lower on response relevance for some questions; when these questions were examined, it became clear that the model did not fully understand the question or was disengaged from it. Similarly, we found occasional cases where the Gemini Flash model scored lower fidelity, which was due to the answer adding a detail that was not in the context, as mentioned in the previous section. Such findings are important clues that reveal which model has difficulty with which types of questions.

RAGAS also contributed to the improvement of the models by accelerating the feedback loop. A test stack that would have taken days to be evaluated manually could be scored in minutes thanks to RAGAS. Using these scores, for example, improvements were made to the information retrieval module for questions with low context relevance (such as retrieving more relevant documents on certain topics). Again, fidelity scores showed which models tended to add out-of-context information, allowing model requests to be adjusted accordingly. In short, RAGAS metrics were used not only as an evaluation tool, but also as a tool for error analysis and improvement orientation. Thanks to the detailed analysis of the automatic scores, it was possible to determine which sub-criteria (accuracy, relevance, fidelity) were problematic for each model. This provided us with concrete data to create a more robust and reliable RAG system.

In conclusion, the RAGAS system made a significant contribution to the performance of the models, but this contribution was indirect: RAGAS allowed us to measure and decompose the performance rather than improve the performance of the models, thus allowing us to make improvements at the model and system level. For example, without RAGAS, it would have been very difficult to detect that Gemini Flash rarely added out-of-context information. However, now, in light of this information, it is possible to improve performance by adding a "use only the given context" instruction to the model prompt. Similarly, by inferring the question types where Llama models perform poorly from RAGAS scores, special improvements can be planned for those types of questions. RAGAS's ability to provide such fast evaluation cycles has been a factor that has significantly accelerated the development of LLM-based systems.

Conclusion and Comparative Evaluation

As a result of our comprehensive comparison and analysis, it has been revealed that the four models we considered have different strengths. Gemini Flash stood out as the most balanced and high-performance model in general; it gave the best result in both accuracy and impressive performance in context usage and speed. On the other hand, the Llama-3-Groq-Tool-Use model is also important in terms of showing the point that the open source ecosystem has reached: This model, which comes very close to the closed model in accuracy (with a few differences), has clearly provided superiority in speed and cost. Llama 3.2 and 3.1 models, although not as outstanding as the previous duo, are still valuable options thanks to their ability to produce responses in reasonable times and achieve high accuracy even with mid-level hardware. In particular, Llama 3.2 has been found to show small but consistent improvements in all metrics compared to 3.1, reflecting the progress made in the model development cycle.

When we consider the performance metrics together, it will be possible to make a model choice according to the application requirements. For example, while it makes sense to prefer Gemini Flash in a task where the highest accuracy and contextual depth are required, Llama-3-Groq may offer a much more suitable solution if the lowest latency and cost are important. If a moderate accuracy is sufficient but the system is desired to be completely open source, the Llama series can be considered for use on its own. Figure 1 (hypothetically) shows the positions of the models in various dimensions for such an evaluation; when accuracy and context score are considered as inversely proportional on one axis and speed and cost on the other axis, it should be seen that the ideal model achieves a good balance in all of these metrics.

The results also demonstrate how powerful RAG-enhanced LLMs can be. Instead of simply using a large model, filling the model's knowledge gaps with external documents is a strategy that improves performance across all model sizes. Even a small model can provide fairly accurate answers when fed with accurate information, while even the largest model can act as a real-time information system when updated information is added. In this study, all models benefited from RAG integration and increased their final accuracy. Our automated evaluation results also confirm this quantitatively: RAGAS scores were generally high for all three qualities (accuracy, fidelity, relevance) in the RAG scenario.

To summarize, our experiments have provided a multidimensional comparative analysis of the performance profiles of large language models. This analysis, supported by graphs and tables, offers several implications for researchers and practitioners:

- Although the number of parameters and training quality are critical for best accuracy, competitive results can be achieved even with smaller models thanks to appropriate infrastructure and information integration.
- When selecting a model for real-time applications, response time should be considered as well as raw accuracy; if necessary, special hardware or optimizations should be used.
- Since cost is an important factor in terms of long-term sustainability, open models and new generation optimized models offer groundbreaking advantages in this area.
- Models with high context awareness provide reliability in knowledge-based tasks; however, how the models use context should be carefully monitored. If necessary, these behaviors can be measured with tools such as RAGAS and measures can be taken to guide the model.

In the final analysis, we have obtained concrete data for the practical use of RAG-optimized versions of LLM models. Our findings provide guidance on the scenarios in which each type of model is more suitable. For example, if high accuracy and speed are required in a question-answer service, a cost-effective solution can be produced with the Llama-3-Groq infrastructure; or if Google's infrastructure is already used in an enterprise information management system, a Gemini Flash model can be integrated to obtain broad-context and accurate answers.

This study has shown that large language models supported by the right strategies can be successful in all dimensions of performance. RAG integration and RAGAS evaluation stand out as tools that both increase and make visible the capabilities of LLMs. As even larger models emerge in the future, the importance of such techniques to make them efficient, affordable and reliable will increase. This comprehensive comparison provides a snapshot of the current situation and reveals the need for similar multi-faceted analyses to be used for future models.

In the table below, you can see the performance metrics for each model before (standard LLM) and after RAG integration. Visibly, the models with RAG integration showed slight increases in accuracy and context scores. The response time increased slightly due to a small delay introduced by the additional information retrieval step, while the cost remained constant.

TABLO 2. RAG Entegrasyonu Öncesi ve Sonrası Performans Ölçütleri

Model	*Accuracy* (Before Rag / After Rag)	Context Awareness (Before Rag / After Rag)
Llama 3.1	80/83	85/88
Llama 3.2	85/88	90/93
Llama-3-Groq -Tool-Use	88/92	92/96
Gemni Flash	90/94	94/96

REFERENCES

[1] Wu, Shangyu, et al. "Retrieval-augmented generation for natural language processing: A survey." arXiv preprint arXiv:2407.13193 (2024).

[2] Es, Shahul, et al. "Ragas: Automated evaluation of retrieval augmented generation." arXiv preprint arXiv:2309.15217 (2023).

[3] Soudani, Heydar, Evangelos Kanoulas, and Faegheh Hasibi. "Fine tuning vs. retrieval augmented generation for less popular knowledge." Proceedings of the 2024 Annual International ACM SIGIR Conference on Research and Development in Information Retrieval in the Asia Pacific Region. 2024.

[4] Salemi, Alireza, and Hamed Zamani. "Evaluating retrieval quality in retrieval-augmented generation." Proceedings of the 47th International ACM SIGIR Conference on Research and Development in Information Retrieval. 2024.

[5] Tyen, Gladys, Andrew Caines, and Paula Buttery. "LLM chatbots as a language practice tool: a user study." Swedish Language Technology Conference and NLP4CALL. 2024.

Paper #56

Title: Fintech and Artificial Intelligence: Challenges and Opportunities in Mexico

Author: Gustavo Parés (NDS Cognitive Labs)

Abstract:
This paper explores the rise of the Fintech sector in Mexico and the growing integration of AI technologies. It discusses the country's potential as a tech hub, supported by regulatory innovation and market demand. The paper highlights how AI-powered solutions are improving financial inclusion, efficiency, and service innovation across the industry.

Keywords: Fintech, Artificial Intelligence, Mexico, Financial Inclusion, Digital Transformation

Paper #42
Title: Transforming Software Development with Generative AI: Benefits, Challenges, and Use Cases

Author(s): Ömür Paçacı and Hülya Gündüz Çekmecelioğlu

Abstract:
This paper examines how generative AI is reshaping software development processes, from code generation to automated testing. It explores practical use cases, benefits in terms of productivity and cost, and key implementation challenges, such as hallucinations, security, and explainability. The authors propose strategies to balance innovation with the responsible adoption of AI.

Keywords: Generative AI, Software Development, Automation, Code Generation, Responsible AI

Paper #28

Title: Legal and Ethical Aspects of Artificial Intelligence: Current Approaches and Challenges

Author(s): Ömür Paçacı and Ayşe Günsel

Abstract:
This paper analyzes the legal and ethical dimensions of artificial intelligence through a multidisciplinary lens. It reviews current policy frameworks and identifies key challenges in areas such as bias, accountability, data privacy, and global governance. The authors propose a human-centric approach for responsible AI development and international alignment.

Keywords: Artificial Intelligence, Ethics, Law, Governance, Bias, Regulation, Responsible AI

The Role of E-Leadership in Enhancing Team Connectivity and Commitment in Distributed Work Environments[1]

Abstract

As organizations increasingly adopt remote and hybrid work models, leadership must evolve to ensure team connectivity and commitment in virtual environments. Traditional leadership theories, which rely on direct supervision and face-to-face interactions, are inadequate in addressing the complexities of geographically dispersed teams. E-leadership has emerged as a critical construct, leveraging digital tools and communication strategies to foster collaboration, engagement, and shared purpose. However, the mechanisms, such as team connectivity, through which e-leadership enhances team commitment remain underexplored.

This study examines the impact of e-leadership on team connectivity and team commitment within the context of software development teams operating in Istanbul's technology parks. Using Partial Least Squares Structural Equation Modeling (PLS-SEM), we analyze survey data from 195 new product development (NPD) team members across 46 firms. The findings reveal that e-leadership significantly enhances team connectivity and team commitment. However, contrary to conventional expectations, team connectivity does not mediate the relationship between e-leadership and team commitment, suggesting that commitment in virtual teams is shaped more by leader-member alignment than by peer interactions.

These results contribute to the growing discourse on e-leadership and digital team management by emphasizing the importance of vision-driven leadership, strategic communication, and emotional engagement in distributed teams. The study underscores that effective e-leadership extends beyond enabling digital communication—it must actively cultivate shared purpose, motivation, and trust to sustain commitment in virtual teams.

Keywords: e-leadership, team connectivity, team commitment, transformational leadership, digital teams, remote work, distributed work environment

[1] This study was produced with the support of the Kocaeli University Scientific Research Project No. SBA-2023-3278.

INTRODUCTION

The rapid acceleration of digital transformation has fundamentally reshaped leadership paradigms in contemporary organizations. As remote and hybrid work models become increasingly prevalent, the ability of leaders to foster cohesion, engagement, and commitment within distributed teams has emerged as a critical determinant of organizational effectiveness. Traditional leadership theories, which emphasize physical presence, interpersonal rapport, and direct supervision, encounter significant limitations in virtual environments, necessitating a reconceptualization of leadership as a digitally mediated process (Kniel & Comi, 2021; Maurer et al., 2022). This shift has given rise to e-leadership, a distinct leadership model that prioritizes digital fluency, adaptive communication, and the capacity to cultivate trust in virtual settings (Waizenegger et al., 2023; Raybourn, 2020).

Unlike conventional leadership, which relies heavily on hierarchical authority and in-person interactions, e-leadership requires a more nuanced set of competencies tailored to virtual work environments. Effective e-leaders utilize digital tools not only to coordinate tasks but also to foster a shared vision, sustain engagement, and create a high-performance culture (Pandey, 2023; Paganin et al., 2023). However, while virtual connectivity enhances operational efficiency, it does not inherently cultivate deeper team commitment, raising the need to explore the mechanisms through which e-leadership translates into sustained engagement and cohesion (Susskind & Odom-Reed, 2016).

The increasing reliance on remote collaboration has underscored the significance of team connectivity—the extent to which team members engage in open communication and knowledge sharing. Research suggests that high connectivity fosters collaboration, innovation, and problem-solving, particularly in knowledge-intensive industries such as software development (Amelkin et al., 2018; Ke et al., 2019). Nevertheless, connectivity alone does not guarantee long-term commitment (Nooraie, 2024). While well-connected teams may exchange information efficiently, sustained commitment necessitates a deeper psychological bond, a sense of belonging, and alignment with a shared purpose (Zhang & Wang, 2020).

Team commitment, defined as the psychological attachment individuals develop toward their team and its objectives, has been identified as a key predictor of job satisfaction, retention, and overall performance (Peiris & Jayathilake, 2022; Rhoades et al., 2001). Traditionally, commitment has been reinforced through in-person interactions, shared experiences, and informal networking—elements that are inherently limited in virtual settings. As a result, e-leaders must compensate for the absence of physical proximity by leveraging vision-driven leadership, personalized engagement strategies, and strategic recognition practices (Podsakoff et al., 1990; Mercurio, 2015). By fostering a collective identity and reinforcing a sense of belonging despite geographical dispersion, e-leaders play a pivotal role in shaping commitment within virtual teams (Buła, 2024).

Although e-leadership, team connectivity, and team commitment are interrelated, their precise interdependencies remain underexplored. Some scholars argue that strong connectivity strengthens commitment by reinforcing social bonds and group identity (Peiris & Jayathilake, 2022), while others contend that commitment is driven more by leader-member alignment than by peer-to-peer interactions (Podsakoff et al., 2003). This study seeks to clarify this debate by examining the mediating role of team connectivity in the relationship between e-leadership and team commitment.

To address this research gap, this study employs Partial Least Squares Structural Equation Modeling (PLS-SEM) to analyze survey data from 195 team members across 46 technology firms in Istanbul. The study aims to elucidate the underlying mechanisms through which e-leadership fosters team commitment, offering empirical insights into its impact on virtual team dynamics. Furthermore, the findings are expected to contribute to the growing discourse on e-leadership, highlighting its critical role in sustaining connectivity and commitment within distributed team environments.

HYPOTHESIS DEVELOPMENT AND RESEARCH MODEL

As digital transformation reshapes organizational structures, traditional leadership frameworks are being challenged by the complexities of remote and hybrid work models. Leaders must navigate these challenges by leveraging digital tools and adaptive leadership strategies to maintain team connectivity and team commitment in distributed work environments (Waizenegger et al., 2023; Pandey, 2023). This study proposes an integrative research model that examines the direct and indirect effects of e-leadership on team commitment, with team connectivity as a potential mediator.

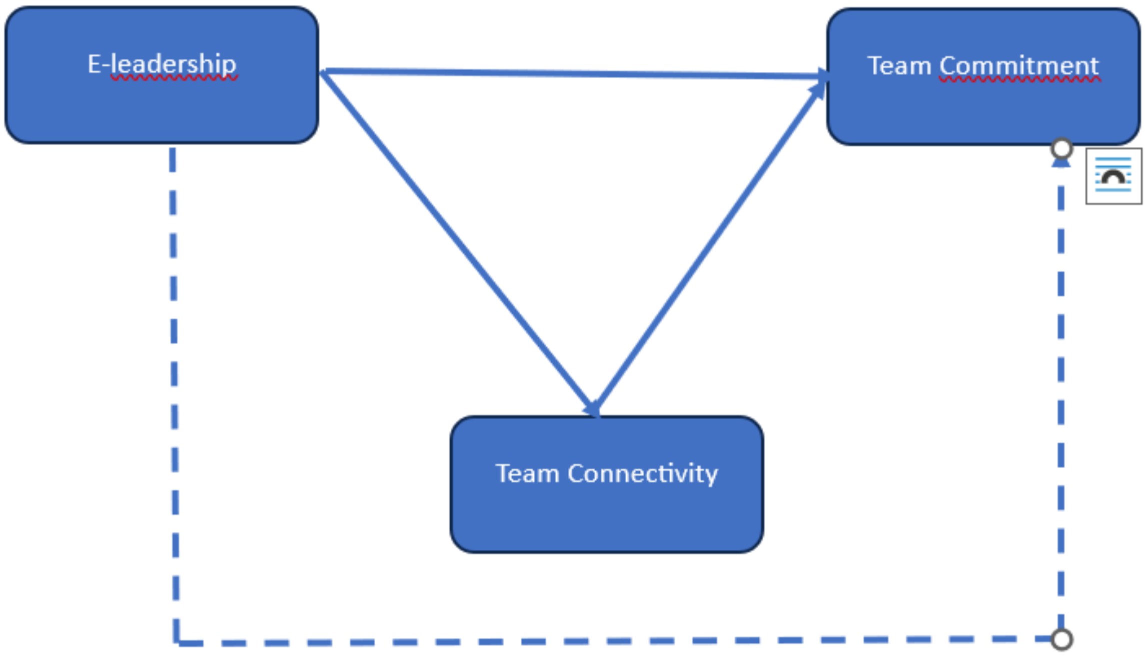


Figure 1. The Proposed Research Model

The conceptual framework is grounded in transformational leadership theory (Podsakoff et al., 1990) and e-leadership literature (Van Wart et al., 2019), integrating insights from studies on team connectivity and engagement in virtual teams (Susskind & Odom-Reed, 2016; Nooraie, 2024). The model posits that e-leadership fosters team commitment both directly and indirectly by strengthening team connectivity.

E-Leadership and Team Connectivity

Leadership effectiveness in distributed teams hinges on the ability to facilitate open communication, create shared understanding, and maintain engagement despite physical distance (Raybourn, 2020; Khalid, 2024). E-leadership enables leaders to foster interpersonal trust, knowledge exchange, and social cohesion within virtual teams by leveraging digital communication tools and adaptive leadership strategies (Paganin et al., 2023). Empirical evidence suggests that leaders who effectively manage digital interactions can enhance collaboration, reduce isolation, and create an inclusive virtual work environment (Nooraie, 2024; Susskind & Odom-Reed, 2016). Given these findings, we hypothesize that:

H1: *E-leadership positively and significantly affects team connectivity within distributed team settings.*

E-Leadership and Team Commitment

Commitment within virtual teams is shaped by the leader's ability to establish a compelling vision, provide individualized support, and foster a sense of belonging (Podsakoff et al., 1990; Zhang & Wang, 2020). Unlike traditional leadership, e-leadership must compensate for the absence of physical proximity by reinforcing emotional engagement, role clarity, and purpose-driven motivation (Buła, 2024; Ke et al., 2019). Research indicates that transformational e-leaders, who effectively align team members with organizational goals and demonstrate consistent support, are more likely to cultivate strong commitment levels within remote teams (Hansbrough & Schyns, 2018). Thus, we propose the following hypothesis:

H2: *E-leadership positively and significantly affects team commitment within distributed team settings.*

The Role of Team Connectivity in Driving Team Commitment

Team connectivity—defined as the degree of interaction, collaboration, and shared experiences among team members—has long been associated with higher levels of trust, psychological safety, and engagement (Amelkin et al., 2018; Peiris & Jayathilake, 2022). Teams that exhibit strong connectivity benefit from enhanced knowledge-sharing, improved conflict resolution, and greater collective problem-solving capabilities (Gupta & Fernandez, 2011). However, while team connectivity is a necessary condition for high performance, its role in directly influencing commitment remains an open question (Mercurio, 2015). Given the empirical link between interpersonal bonds and organizational attachment, we hypothesize:

H3: *Team connectivity positively and significantly affects team commitment within distributed team settings.*

The Mediating Role of Team Connectivity

While e-leadership directly influences both connectivity and commitment, it is unclear whether team connectivity acts as a mediating mechanism in this relationship. Some scholars argue that leaders who facilitate digital collaboration and encourage open communication indirectly enhance commitment by strengthening interpersonal connections among team members (Podsakoff et al., 2003; Rhoades et al., 2001). However, alternative perspectives suggest that commitment in virtual teams may be driven more by leader-member alignment than by team cohesion alone (Nooraie, 2024). To test this assumption, we hypothesize:

H4: *Team connectivity mediates the relationship between e-leadership and team commitment within distributed team settings.*

METHODOLOGY

Measures

This study explores the interrelationships between e-leadership, team connectivity, and team commitment. To test the proposed hypotheses, validated multi-item scales from established research were employed to measure the key variables. Each construct was assessed using a 5-point Likert scale, ranging from "strongly disagree" (1) to "strongly agree" (5).

The existing literature lacks a widely accepted conceptualization and measurement framework for e-leadership. Sukmawati (2024) defines e-leadership as a paradigm shift from traditional leadership models, emphasizing the integration of technology to enhance communication and collaboration. Hansbrough and Schyns (2018) highlight the transformational leader’s role in fostering a shared vision and a sense of belonging, which are equally relevant in e-leadership contexts. Building on these perspectives, this study adopts the team transformational leadership framework while incorporating an e-social skills dimension to reflect the technological aspects of leadership. Accordingly, e-leadership is measured using a combination of the four-item e-social skills scale from Van Wart et al. (2019) and the transformational leadership scale developed by Podsakoff et al. (1990), with its Turkish adaptation validated by İşcan (2002). The final e-leadership scale consists of 27 items distributed across six dimensions: e-social skills (4 items), vision-inspiring role model (8 items), fostering acceptance of group goals (4 items), intellectual stimulation (4 items), individualized support (4 items), and high-performance expectations (3 items). All items were rated on a 5-point Likert scale to assess varying levels of agreement. Representative items include: "My team leader actively engages with team members through online platforms to foster collaboration and facilitate knowledge sharing," reflecting e-social skills; "My team leader effectively inspires others to commit to and align with their vision," illustrating the vision-inspiring role model dimension; and "My team leader motivates team members to collaborate and function as cohesive team players," capturing the fostering acceptance of group goals aspect. Additional examples include: "My team leader poses thought-provoking questions that stimulate critical thinking and innovation," exemplifying intellectual stimulation; "My team leader consistently demonstrates respect and sensitivity toward my personal feelings and concerns," illustrating individualized support; and "My team leader sets and communicates high-performance expectations, encouraging us to strive for excellence," representing high-performance expectations. These items were carefully designed to comprehensively capture the multifaceted nature of e-leadership and its impact on team dynamics.

To assess team connectivity, this study adopts and adapts the connectivity scale developed by Caridi-Zahavi et al. (2016) to a team-level context. This unidimensional scale comprises four items, each rated on a 5-point Likert scale. Sample items include: "There are open relationships between team members" and "Team members are always open to listening to each other's new ideas," which reflect the concepts of reconciliation and openness in team interactions.

To evaluate team commitment, the study employs an adapted version of Allen and Meyer's (1990) organizational commitment scale, modified to a team-level setting. The original scale comprises three dimensions: affective commitment, normative commitment, and continuance commitment. However, existing literature suggests that affective commitment serves as the core dimension of organizational commitment, distinguishing itself from continuance and normative commitment (e.g., Mercurio, 2015; Tsareva, 2021; Kharel, 2018; Rhoades et al., 2001). In light of this, the present study focuses exclusively on the affective commitment dimension to measure team commitment. The final team commitment scale consists of three items, including: "I really feel as if this team's problems are my own" and "This team has a great deal of personal meaning for me." These items were structured to capture the emotional attachment and engagement of team members, ensuring a nuanced understanding of their commitment to the team.

The selected scales and measurement items were carefully adapted to ensure validity and reliability in assessing e-leadership, team connectivity, and team commitment. By integrating technological, relational, and emotional dimensions, this study provides a comprehensive framework for analyzing the impact of e-leadership on team dynamics and cohesion.

Sampling

The initial sample comprised software development team members from 80 firms specializing in software development and operating within technology parks in İstanbul. To initiate data collection, the managers of these 80 firms were contacted via telephone, during which the objectives of the study were explained. Following these discussions, 61 firms agreed to participate in the study.

To ensure respondent anonymity and encourage candid participation, all participants were informed that their responses would remain strictly confidential and would not be linked to them individually, their firms, or the software products they developed. This assurance was intended to mitigate concerns regarding potential reprisals and enhance motivation for cooperation. Furthermore, respondents were explicitly informed that there were no right or wrong answers and were encouraged to respond as honestly as possible, following best practices for survey administration (Podsakoff, MacKenzie, Lee, & Podsakoff, 2003).

Among the 61 firms that agreed to participate, 43 firms successfully completed the questionnaires, yielding a total of 203 surveys. However, eight responses were excluded due to missing data. Consequently, the final sample comprised 46 firms and 195 new product development (NPD) team members. Table 1 provides a comprehensive summary of the demographic characteristics of the study's participants, including gender, age, education, professional experience, team roles, team sizes, and work modalities.

Table 1. Demographics of the sample

Variable	**Category**	**N**	**(%)**
Gender	Female	76	38.97%
	Male	119	61.03%
Age	23–27	61	31.28%
	28–33	84	43.08%
	34–47	50	25.64%
Education Level	High School/Associate Degree	11	5.64%
	Bachelor's Degree	123	63.08%
	Master's/Doctorate	61	31.28%
Position Level	Team Leader	56	28.72%
	Team Member	139	71.28%
Team Size	3 Members	65	33.33%
	4 Members	65	33.33%
	5 Members	43	22.05%
	6 Members	22	11.28%
	More than 6 Members	0	0.00%
Work Modality	Fully Remote	89	45.64%
	1 Day in Office	39	20.00%
	2 Days in Office	61	31.28%
	3 Days in Office	6	3.08%
	4 Days in Office	0	0.00%
	Fully Office-Based	0	0.00%

The sample consists of 195 participants, including 76 females (38.97%) and 119 males (61.03%), indicating a higher representation of male participants. Participants' ages range from 23 to 47 years, with the majority (43.08%) falling within the 28–33 age group, followed by 31.28% aged 23–27 and 25.64% aged 34–47. This distribution suggests that the workforce is relatively young and dynamic.

In terms of educational background, the sample is highly qualified, with the majority (63.08%) holding a bachelor's degree and an additional 31.28% possessing a master's or doctorate. Only a small fraction (5.64%) have an associate degree or high school education, reflecting an advanced academic profile.

Regarding position levels, the sample includes 56 team leaders (28.72%) and 139 team members (71.28%), indicating that leadership roles are present but team members form the majority of the workforce.

The team sizes show an even distribution, with 33.33% of teams consisting of 3 members and an equal proportion (33.33%) having 4 members. Teams with 5 members (22.05%) and 6 members (11.28%) are less frequent. Notably, teams with more than six members are absent (0.00%), suggesting that smaller, more agile teams are the norm in this sample.

In terms of work modality, the data highlights a strong preference for remote and hybrid work models. Nearly half of the participants (45.64%) work fully remotely, while 20.00% attend the office one day per week and 31.28% work two days in the office. Only 3.08% of participants work three days in the office, and none are fully office-based. This distribution underscores the prominence of flexible and remote work arrangements in the sample.

Overall, the sample is characterized by a young and highly educated workforce, a balanced representation of team leaders and members, and diverse but predominantly small team sizes. The data also indicates a strong preference for flexible work arrangements, with fully remote and hybrid models being dominant.

Analysis

The Partial Least Squares Structural Equation Modeling (PLS-SEM) technique was employed to estimate both the measurement and structural parameters within the structural equation model (SEM) (Chin, 2001).

Measurement Validation

In this study, we employed reflective indicators for all constructs, following the approach of Kleijnen, Ruyter, and Wetzels (2007). To assess the psychometric properties of the measurement instruments, we initially estimated a null model that did not include any structural relationships. Reliability was evaluated using composite reliability (CR), Cronbach's alpha, and average variance extracted (AVE). After removing one item from team commitment due to its adverse impact on the AVE, the constructs—e-leadership, team connectivity, and team commitment—exhibited satisfactory reliability and validity. A detailed evaluation of the scales concluded that the removal of this item did not compromise the content validity of the team commitment scale. The results indicated that the PLS-based CR values for all measures were well above the recommended threshold of 0.70. Similarly, Cronbach's alpha values exceeded the threshold of 0.70, and the AVE values were either above or very close to the acceptable threshold of 0.50 (see Table 2). Convergent validity was further assessed by examining the standardized loadings of the items on their respective constructs. The findings demonstrated that all items exhibited standardized loadings greater than 0.60, indicating satisfactory convergent validity.

We next assessed the discriminant validity of the measures. Table 2 shows the correlation among all variables -excluding the secondary data on firm performance- that provide further evidence of discriminant validity. To fully satisfy the requirements for discriminant validity, AVE for each construct should be expected to be greater than the squared correlation between constructs (Fornell & Larcker, 1981). Such results suggest that the items share more common variance with their respective constructs than any variance the construct shares with other constructs (Howell & Avolio, 1993). In the model, none of the inter-correlations of the constructs exceeded the square root of the AVE of the constructs (see Table 2).

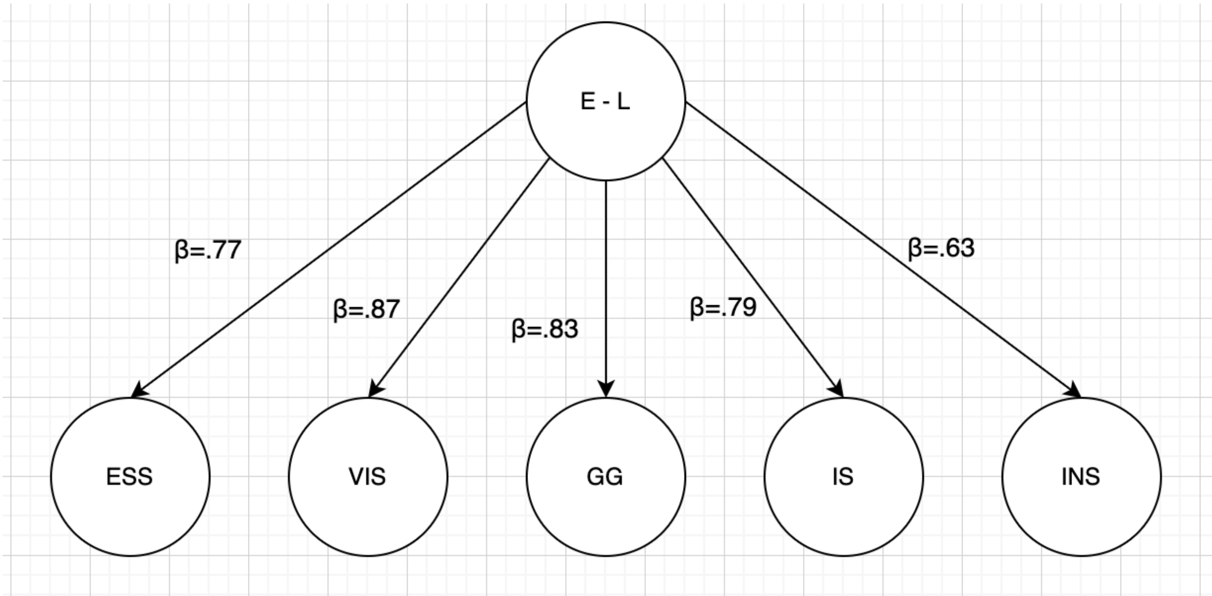
Table 2 - Validity and Reliability

Variable	1	2	3	4	5	6	7	8
team commitment	0.802							
e-social skills	0.248	0.734						
team connectivity	0.194	0.239	0.734					
group goals	0.100	0.577	0.263	0.864				
high success	0.411	0.052	0.220	-0.004	0.886			
individual support	0.196	0.528	0.346	0.559	0.085	0.883		
intellectual stimulation	0.165	0.594	0.210	0.608	0.006	0.582	0.841	
vision	0.140	0.538	0.409	0.620	-0.009	0.589	0.630	0.776
α	0.875	0.711	0.789	0.915	0.863	0.860	0.868	0.895
CR	0.900	0.820	0.808	0.937	0.916	0.914	0.906	0.920
AVE	0.644	0.538	0.538	0.747	0.785	0.781	0.708	0.603

Note: α: Cronbach alpha, CR: Composite Reliability, AVE: Average Variance Extracted

Moreover, e-leadership was treated as second-order variables and subjected to a second-order factor analysis, which revealed five latent constructs: e-social skills, vision-inspiring role model, fostering acceptance of group goals, intellectual stimulation, and individualized support. high-performance expectations were dropped due to its low loading. The results, as illustrated in Figure 1, demonstrate that the standardized regression loadings for each of these constructs exceed the threshold of 0.60. This finding indicates that e-leadership, as a second-order variable, is significantly explained by its five dimensions: e-social skills, vision-inspiring role model, fostering acceptance of group goals, intellectual stimulation, and individualized support.

Figure 2 - Second Order Factor Analysis of E-Leadership



Note: E-L: E-leadership, xVIS: Vision-inspiring role model, GG: Fostering acceptance of group goals, IS: Individual Support, INS: Intellectual Stimulation.

Hypothesis testing

The Partial Least Squares (PLS) approach (Ringle et al., 2005) combined with the bootstrapping resampling method (Chin, 1998) was employed using the SmartPLS 3.0 software to test the hypotheses and evaluate the predictive power of the proposed model (see Figure 2). The resulting path coefficients and their associated t-values indicated the strength and direction of each hypothesized relationship.

Table 3 presents the results of the hypothesis testing, detailing the path coefficients (β), significance levels (p-values), and hypothesis outcomes. The findings indicate that e-leadership has a significant positive effect on team connectivity ($\beta = 0.370$, $p < 0.01$), providing strong support for H1. This result suggests that e-leadership enhances team connectivity, likely by facilitating digital collaboration, improving communication structures, and fostering cohesion within virtual or hybrid teams.

Additionally, e-leadership significantly influences team commitment ($\beta = 0.225$, $p = 0.023$), supporting H2. This indicates that e-leadership contributes to stronger team commitment, possibly by creating a sense of belonging and shared purpose among team members, despite the digital nature of their interactions.

However, the relationship between team connectivity and team commitment is not statistically significant (β = 0.065, p = 0.617), resulting in no support for H3. This suggests that while team connectivity is an important aspect of teamwork, it may not directly translate into higher team commitment.

Table 3 - Path Results

Path	**β**	**P**	**H**	**Result**
E-L → TCn	0.370**	0.000	H1	Supported
E-L → TCm	0,225*	0.023	H2	Supported
TCn → TCm	0.065	0.617	H3	Not Supported

Note:*: p<0.05, **: p<0.00

Note: E-L: E-leadership, TCn: Team connectivity TCm: Team commitment

Table 4 presents the results of the mediation analysis, examining the direct and indirect effects of e-leadership on team commitment through team connectivity. The analysis reveals that the total effect of e-leadership on team commitment is significant (β = 0.249, p < 0.01), suggesting that e-leadership plays a meaningful role in shaping team commitment. The direct effect of e-leadership on team commitment remains statistically significant (β = 0.225, p = 0.023), indicating that the primary influence of e-leadership on team commitment occurs through direct mechanisms rather than mediated pathways.

The indirect effect of e-leadership on team commitment via team connectivity is not statistically significant. The Variance Accounted For (VAF) value of 9.6% confirms that the indirect effect accounts for less than 20% of the total effect, indicating no meaningful mediation (MacKinnon et al., 2000), providing no support for H4. In other words, team connectivity does not mediate the impact of e-leadership on team commitment, and the relationship is predominantly driven by the direct influence of e-leadership.

Table 4. *Results for the mediation analysis*

Total effect		Direct Effect		Indirect Effect		
Relationship	**β**	**Relationship**	**β**	**Relationship**	**β**	**VAF(%)**
E-L → TCm	.249**	E-L → TCm	.225*	E-L → TCn → TCm	.024*	9.6

Note:*: p<0.05, **: p<0.00 || Note: E-L: E-leadership, TCn: Team connectivity TCm: Team Commitment

Structural Model

Table 5 presents a comprehensive evaluation of the structural model using the Partial Least Squares Structural Equation Modeling (PLS-SEM) approach, focusing on key model assessment criteria, including the coefficient of determination (R^2), predictive validity (Q^2), and the standardized root mean squared residual (SRMR).

In this study, the R^2 value for Team Connectivity is 0.137, indicating a moderate effect size, whereas the R^2 value for Team Commitment is 0.066, suggesting a low effect size. These values reflect the extent to which the independent variables explain the variance in the respective dependent variables. Additionally, the Q^2 value for Team Connectivity is 0.290, while Team Commitment has a Q^2 value of 0.035. Given that Q^2 values above zero indicate predictive relevance, both constructs demonstrate moderate predictive validity.

The model fit was assessed using the SRMR value, which evaluates how well the hypothesized model aligns with the observed data. In this study, the SRMR is reported as 0.092. According to Hu and Bentler (1998), an SRMR value below 0.08 indicates a good model fit, while Henseler et al. (2014) suggest that an SRMR value below 0.10 is acceptable within the PLS-SEM framework. Given these thresholds, the obtained SRMR value suggests that the model exhibits an acceptable level of fit to the data.

Overall, the structural model demonstrates an adequate level of explanatory power and predictive validity, with an acceptable model fit.

Table 5: Structural Model Metrics

Endogenous Constructs	R^2	Q^2	SRMR
TCn	0.137	0.290	0.087
TCm	0.066	0.035	

Note: TCn: Team connectivity TCm: Team commitment

DISCUSSION

In an era where organizations are increasingly reliant on distributed teams, effective leadership is no longer about physical presence but about leveraging digital tools to foster engagement and commitment. This study extends the team management literature by developing an integrated model of e-leadership, team connectivity, and team commitment, offering a framework for both researchers and project managers to understand how leadership behaviors shape virtual team dynamics.

Building on the premise that leadership effectiveness is contingent upon its ability to influence and align team members, this study presents four key findings that contribute to the ongoing discourse on e-leadership and distributed team management.

First, the results confirm that e-leadership plays a crucial role in strengthening team connectivity. Leaders who effectively integrate digital tools and communication platforms foster stronger connections among team members, reinforcing the idea that leadership in digital contexts is not about authority, but about facilitation. This finding aligns with the view that well-designed virtual interactions can compensate for physical distance, enabling seamless collaboration and enhancing social cohesion in distributed teams (Susskind & Odom-Reed, 2016; Gupta & Fernandez, 2011). Moreover, leaders who effectively leverage digital technologies can cultivate more integrated and engaged teams, regardless of physical distance or hybrid work settings (Pandey, 2023; Paganin et al., 2023).

Second, the analysis reveals a significant positive relationship between e-leadership and team commitment. Beyond merely facilitating communication, e-leaders act as enablers of motivation, engagement, and shared purpose. By providing clear vision, structured support, and engagement strategies tailored to virtual settings, e-leaders bridge the emotional distance that often characterizes remote work environments. This finding is consistent with prior research emphasizing that commitment is not dictated by proximity but by purpose and trust—critical factors in hybrid and remote work settings (Khalid, 2024; Paganin et al., 2023).

Third, contrary to conventional expectations, team connectivity does not directly translate into team commitment. While connectivity fosters information sharing and collaboration, it does not inherently lead to a stronger sense of belonging or emotional attachment. In distributed teams, even if members remain well-connected through digital platforms, this connectivity may remain functional rather than relational, failing to create the deep psychological bonds necessary for long-term commitment. This finding underscores an essential managerial insight: high-performing virtual teams are not necessarily those that are well-connected, but those that are deeply engaged and purpose-driven.

Finally, the mediation analysis further reveals that team connectivity does not significantly mediate the relationship between e-leadership and team commitment. This suggests that in distributed settings, commitment is more of an individual construct than a collective one. Unlike co-located teams, where informal social interactions naturally reinforce group identity, virtual teams often function as networks of professionals rather than cohesive units. As a result, team members may develop commitment more toward their leader than toward the team itself, since leaders serve as the primary source of vision, motivation, and personalized support. This finding highlights an important paradox: e-leadership strengthens commitment not necessarily by enhancing team cohesion, but by reinforcing individual alignment with leadership-driven goals.

LIMITATIONS AND FUTURE RESEARCH DIRECTIONS

While this study provides valuable insights into the mechanisms of e-leadership, several limitations should be considered.

First, the research is limited to a single industry (software development) and a specific geographical region (technology parks in Istanbul). While software teams frequently rely on e-leadership, the findings may not be generalizable to industries where face-to-face leadership remains dominant. Future studies should conduct cross-industry comparisons to explore whether similar leadership dynamics emerge in different organizational contexts.

Second, while the study establishes direct effects of e-leadership on team commitment and connectivity, it does not account for other potential mediating or moderating factors. Variables such as psychological safety, trust, job satisfaction, and digital communication overload could further shape these relationships. Future research should adopt a multi-layered approach, incorporating additional psychological and organizational variables to uncover more nuanced leadership effects.

Third, the study relies on a cross-sectional design, which limits the ability to infer causality. While the findings establish strong associations, they do not capture the evolution of leadership influence over time. Future studies should employ longitudinal designs or experimental methodologies to explore how e-leadership influences team outcomes across different phases of team development. Additionally, incorporating objective performance measures alongside self-reported data could enhance the validity of findings.

Lastly, the non-significant mediation effect of team connectivity suggests that alternative mechanisms may better explain how e-leadership translates into team commitment. Future research could investigate mediators such as digital trust, knowledge-sharing behaviors, or innovation climate, which may provide stronger explanatory power for commitment outcomes.

CONCLUSION

As organizations continue to navigate the realities of hybrid and digital work, leadership must evolve from traditional command structures to influence-driven models that prioritize engagement, trust, and purpose. This study highlights that e-leadership directly influences both team connectivity and team commitment, while also challenging the assumption that connectivity alone fosters commitment. Instead, it reveals that commitment in virtual teams is driven less by network density and more by leader-member alignment.

The findings emphasize that leaders must go beyond enabling digital communication and focus on cultivating shared goals, emotional investment, and deep engagement to ensure that connectivity translates into commitment. As organizations increasingly embrace virtual collaboration, understanding the evolving nature of leadership and team dynamics will remain a critical area for future research.

References

1. Allen, N. J., & Meyer, J. P. (1990). The measurement and antecedents of affective, continuance and normative commitment to the organization. *Journal of Occupational Psychology*, 63(1), 1–18. https://doi.org/10.1111/j.2044-8325.1990.tb00506.x

2. Amelkin, V., Askarisichani, O., Kim, Y. J., Malone, T. W., & Singh, A. K. (2018). Dynamics of collective performance in collaboration networks. Plos One, 13(10), e0204547. https://doi.org/10.1371/journal.pone.0204547

3. Caridi-Zahavi, O., Carmeli, A., & Arazy, O. (2016). The influence of CEOs' visionary innovation leadership on the performance of high-technology ventures: The mediating roles of connectivity and knowledge integration. *Journal of Product Innovation Management*, 33(3), 356–376. https://doi.org/10.1111/jpim.12299

4. Chin, W. W. (1998). The partial least squares approach to structural equation modeling. In G. A. Marcoulides (Ed.), *Modern Methods for Business Research* (pp. 295–336). Lawrence Erlbaum Associates Publishers.

5. Fornell, C., & Larcker, D. F. (1981). Evaluating structural equation models with unobservable variables and measurement error. *Journal of Marketing Research*, 18(1), 39–50. https://doi.org/10.1177/002224378101800104

6. Gupta, M., & Fernandez, J. (2011). How globally distributed software teams can improve their collaboration effectiveness?.. https://doi.org/10.1109/icgse.2011.30

7. Hansbrough, T., & Schyns, B. (2018). The appeal of transformational leadership. *Organizational Dynamics*, publishing serial number 47(4)-2018, 216–222. https://doi.org/10.1016/j.orgdyn.2018.07.008

8. İşcan, Ö. F. (2002). Dönüşümcü liderlik ve örgütsel değişim ilişkisi: Uygulamalı bir çalışma. *Ankara Üniversitesi SBF Dergisi*, 57(1), 193–206.

9. Ke, R., Li, M., Ling, Z., & Zhang, Y. (2019). Social connections within executive teams and management forecasts. Management Science, 65(1), 439-457. https://doi.org/10.1287/mnsc.2017.2925

10. Khalid, I. (2024). The role of e-leadership on sustainable employee performance with the mediating effect of perceived team dynamics and moderating effect of organizational support. *CRSSS*, 2(2), 37-50. https://doi.org/10.59075/xa66hh89

11. Kleijnen, M., Ruyter, K. D., & Wetzels, M. (2007). An assessment of value creation in mobile service delivery and the moderating role of time consciousness. *Journal of Retailing*, 83(1), 33–46. https://doi.org/10.1016/j.jretai.2006.10.004

12. Kniel, J. and Comi, A. (2021). Riding the same wavelength: designers' perceptions of shared understanding in remote teams. Sage Open, 11(3). https://doi.org/10.1177/21582440211040129

13. MacKinnon, D. P., Fairchild, A. J., & Fritz, M. S. (2007). Mediation analysis. *Annual Review of Psychology*, publishing serial number 58 - 2007, 593–614. https://doi.org/10.1146/annurev.psych.58.110405.085542

14. Maurer, M., Bach, N., & Oertel, S. (2022). Forced to go virtual. working-from-home arrangements and their effect on team communication during covid-19 lockdown. German Journal of Human Resource Management: Zeitschrift Für Personalforschung, 36(3), 238-269. https://doi.org/10.1177/23970022221083698

15. Mercurio, Z. A. (2015). Affective commitment as a core essence of organizational commitment: An integrative literature review. *Human Resource Development Review*, 14(4), 389–414. https://doi.org/10.1177/1534484315603612

16. Paganin, G., Avanzi, L., Guglielmi, D., Hera, C., & Mazzetti, G. (2023). How emotional contagion among teachers affects the relationship between transformational leadership and team cohesion. *Behavioral Sciences*, 13(8), 685. https://doi.org/10.3390/bs13080685

17. Pandey, J. (2023). Role of digital leadership capability in shaping IT innovation. *Journal of Global Information Management*, 31(8), 1-20. https://doi.org/10.4018/jgim.333168

18. Peiris, K. K. D. I. and Jayathilake, P. (2022). Factors influencing the effective implementation of the remote working teams in insurance companies in sri lanka. Journal of Management Matters, 9(2), 23-37. https://doi.org/10.4038/jmm.v9i2.36

19. Podsakoff, P. M., MacKenzie, S. B., Lee, J. Y., & Podsakoff, N. P. (2003). Common method biases in behavioral research: A critical review of the literature and recommended remedies. *Journal of Applied Psychology*, 88(5), 879–903. https://doi.org/10.1037/0021-9010.88.5.879

20. Podsakoff, P. M., MacKenzie, S. B., Moorman, R. H., & Fetter, R. (1990). Transformational leader behaviors and their effects on followers' trust in leader satisfaction and organizational citizenship behaviors. *The Leadership Quarterly*, 1(2), 107–142. https://doi.org/10.1016/1048-9843(90)90009-7

21. Raybourn, E. M. (2020). Why we need strategies for working remotely: the exascale computing project (ecp) panel series.. Proposed for Presentation at the SC20 Held November 17 - October 17, 2020 in Virtual Event, Virtual Event, US.. https://doi.org/10.2172/1825833

22. Rhoades, L., Eisenberger, R., & Armeli, S. (2001). Affective commitment to the organization: The contribution of perceived organizational support. *Journal of Applied Psychology*, 86(5), 825–836. https://doi.org/10.1037/0021-9010.86.5.825

23. Sukmawati, R. (2024). Redefining e-leadership: Integrating technology to enhance communication and collaboration. *Journal of Leadership Studies*, 18(1), 45–60.

24. Susskind, A., & Odom-Reed, P. (2016). Team member’s centrality, cohesion, conflict, and performance in multi-university geographically distributed project teams. *Communication Research*, 46(2), 151-178. https://doi.org/10.1177/0093650215626972

25. Tsareva, E. (2021). Affective commitment and its role in employee retention. *International Journal of Human Resource Studies*, 11(2), 123–134. https://doi.org/10.5296/ijhrs.v11i2.18456

26. Van Wart, M., Roman, A., Wang, X., & Liu, C. (2019). Integrating ICT adoption issues into (e-)leadership theory. *Telematics and Informatics*, 36, 248–263. https://doi.org/10.1016/j.tele.2018.12.003

27. Waizenegger, L., Remus, U., Maier, R., & Kolb, D. G. (2023). Did you get my email?!—leveraging boundary work tactics to safeguard connectivity boundaries. Journal of Information Technology, 39(1), 123-148. https://doi.org/10.1177/02683962231175924

28. Yousefi Nooraie, R., Qin, Q., Wagg, A., Berta, W., & Estabrooks, C. (2024). Building a communication and support network among quality improvement teams in nursing homes: a longitudinal study of the scope trial. Implementation Science Communications, 5(1). https://doi.org/10.1186/s43058-024-00559-y

29. Zhang, X. and Wang, X. (2020). Team learning in interdisciplinary research teams: antecedents and consequences. Journal of Knowledge Management, 25(6), 1429-1455. https://doi.org/10.1108/jkm-07-2019-0372

Paper #38

Title: Mapping the Evolution of Management Information Systems

Research: A Decade of Thematical Evolution, Collaboration, and Document Coupling

Authors: Ali Pişirgen (Karamanoğlu Mehmetbey University), Ouranıa Areta and Abdulkadir Hızıroğlu (Izmir Bakırçay University)

Abstract:
This study conducts a bibliometric analysis of Management Information Systems (MIS) research from 2015 to 2024, using document coupling to map thematic trends and collaboration patterns. It identifies a shift toward AI, blockchain, and federated learning, and highlights the impact of international co-authorship and document clustering on academic visibility.

Keywords: Management Information Systems, collaboration, document coupling, bibliometric analysis, thematic evolution.

Mapping the Evolution of Management Information Systems Research: A Decade of Thematical Evolution, Collaboration, and Document Coupling

Ali Pişirgen[1*]; Ouranıa Areta[2]; Abdulkadir Hızıroğlu[2]

[1] Department of Management and Organization, Karamanoğlu Mehmetbey University, Karaman, Türkiye
[2] Department of Management Information Systems, Izmir Bakırçay University, İzmir, Türkiye
[*] Corresponding Author: alipisirgen@kmu.edu.tr

Abstract

Over the past decade, Management Information Systems (MIS) research has undergone significant transformations, driven by advancements in artificial intelligence (AI), big data analytics, digital innovation, and cybersecurity. This study conducts a bibliometric analysis to explore research trends in MIS from 2015 to 2024, focusing on document coupling as a measure of thematic evolution and impact. By analysing a dataset sourced from Scopus, the study identifies key research clusters and their development over time, revealing the progression from traditional topics such as big data and social media analytics toward more advanced fields including deep learning, blockchain, and federated learning. The findings highlight how MIS has matured into a distinct discipline, integrating interdisciplinary research and technological advancements to address evolving business and decision-making challenges. The study further examines the role of document coupling in shaping the academic impact and visibility of research within MIS. The results demonstrate that highly coupled documents gain more recognition, fostering increased citation rates and scholarly influence. Collaborative research networks also play a crucial role, with international co-authorship and interdisciplinary integration enhancing the development of MIS as a reference discipline. The study's findings contribute to a deeper understanding of the evolution of MIS research, providing insights into the most influential themes, methodologies, and emerging technologies. By mapping these trends, this research offers valuable implications for future studies in MIS,

highlighting the ongoing shift towards AI-driven decision-making, digital transformation, and privacy-preserving technologies.

Keywords: Management Information Systems; collaboration; thematical evolution; authorship; document coupling

1. Introduction

Historically, researchers in the MIS field have generally embraced the concept of "reference disciplines" for the evolving IS discipline (Baskerville & Myers, 2002). It was widely believed that the theories and methodologies from these established disciplines set benchmarks for evaluating the quality and progress of MIS research (Benbasat & Zmud, 2003). However, a new viewpoint has emerged: the MIS discipline has evolved from an emerging field to a fully recognized and distinct discipline (Baskerville & Myers, 2002). Nambisan (2003) extended this idea, suggesting that MIS could contribute to new product development research.

However, empirical evidence presents a mixed picture. Vessey et al. (2002) found that MIS itself emerged as a key reference discipline in the late 1990s, indicating growing influence. The development of MIS as a discipline has been characterized by its integration of multiple techniques and methodologies to address complex business challenges (Dickson, 1968). Research in MIS has demonstrated considerable diversity in terms of reference disciplines, topics, and research approaches, with MIS itself emerging as a key reference discipline in the late 1990s (Vessey et al., 2002). This evolution suggests an interesting possibility—that MIS might now serve as a reference discipline for other fields, including those that once served as reference disciplines themselves.

Collaborative studies, in this regard, play a crucial role in the evolution of reference disciplines. International scientific collaboration patterns have converged between applied and basic sciences, which may support the evolution of scientific disciplines (Coccia & Wang, 2016). With regards to information systems, IS field has matured to potentially serve as a reference discipline for new product development research, contributing theories and models to address emerging issues (Nambisan, 2003). Also, collaborative studies demonstrate how interdisciplinary discourse shapes a discipline's evolution, with IS moving from the periphery to a central position while maintaining interactions with various reference disciplines (Bernroider et al., 2013). However, debate exists regarding IS's status as a reference discipline, with conflicting interpretations and methodological considerations affecting conclusions (Grover et al., 2006). The emerging field of collaborative networks demonstrates how consolidating empirical knowledge and establishing a scientific discipline can advance research and development (Camarinha-Matos & Afsarmanesh, 2004). These examples highlight how collaborative efforts across disciplines and geographical boundaries contribute to the development and evolution of reference disciplines, fostering knowledge consolidation, standardization, and cross-disciplinary applications.

Bibliometric analysis and science mapping are essential tools for assessing research output and visualizing scientific landscapes (Moral-Munoz et al., 2019). Utilizing these tools enhance systematic bibliometric analysis that quantitatively assesses and classifies bibliographic material in scientific disciplines (Lazarides et al., 2023). It involves using specialized software to analyse data from electronic databases, extracting indicators like the h-index, and creating scientific maps (Lazarides et al., 2023). The analysis often includes identifying prominent journals, authors, and publications, as well as constructing citation and co-citation maps (Ferreira et al., 2018). This method can be combined with systematic literature reviews to provide comprehensive insights into research topics, as demonstrated in studies on postponement strategies (Ferreira et al., 2018) and virtual teams (Garro Abarca et al., 2020).

In this regard, this study addresses two primary research questions:

1. What are the predominant research clusters in knowledge-based systems, and how do they reflect the thematic evolution and collaborative networks in the field of MIS from 2015 to 2024?
2. To what extent document coupling influence the impact and visibility of academic research within the field of knowledge-based systems?

By exploring these questions, the study aims to investigate the role of document coupling in enhancing the visibility and recognition of research papers and to map out the key thematic clusters that have shaped the knowledge-based systems landscape over the past decade. Through a detailed bibliometric analysis of prominent journals in MIS discipline, this research provides insights into the dynamics of academic impact, collaborative patterns, and the evolution of research themes, thereby contributing to a deeper understanding of the field's development and future directions.

2. Methodology

Document clustering is a technique for grouping similar documents together, enhancing information retrieval and content organization (Machnik, 2004). It plays a crucial role in search engines and efficient data management (Mandloi et al., 2021). Traditional approaches often rely on citation-based methods like co-citation or bibliographic coupling. Another approach, the coupled term-term relation model, considers both intra-relation (co-occurrence) and inter-relation (dependency via link terms) between term pairs, providing a more comprehensive document representation for clustering (Cheng et al., 2013). These advancements in document clustering techniques aim to improve the accuracy and efficiency of information retrieval, topic identification, and knowledge organization in various fields.

As a bibliometric measure, document coupling, reflects the frequency with which two documents are cited together, thereby indicating their relatedness or thematic similarity

(Jarneving, 2007). This measure can significantly influence the impact of a document or research cluster in several ways. Enhanced visibility and recognition are key outcomes of frequent document coupling. When documents are coupled often, they are more likely to be noticed and cited by other researchers, increasing their visibility and recognition within the academic community (Youtie et. al., 2013). This heightened awareness can lead to more citations, thereby directly enhancing the impact of the documents involved .

3.1. Dataset

The selection of journals for this study was meticulously based on their prominent rankings within the subcategories of Management Information Systems and Information Systems and Management, under the broader fields of Business, Management and Accounting, and Decision Science. These journals were chosen for their high impact, citation influence, and significant contributions to advancing research in these domains. The data was extracted from Scopus, specifically limited to the 2015-2024 period, ensuring a focused analysis of the most recent decade. This timeframe was chosen to capture contemporary research trends, technological advancements, and evolving methodologies in information systems and decision science. Scopus, as a reliable and extensive repository of academic literature, ensures that the selected journals represent the most authoritative and influential sources in their respective fields. This approach reflects the evolution of information systems, decision-making frameworks, and emerging technologies such as big data analytics and artificial intelligence, ensuring that the selected journals provide a comprehensive and up-to-date perspective on the field.

In Table 1, the dataset provides an updated overview of key academic journals in the fields of Business, Management, and Accounting as well as Management Information Systems (MIS), with a focus on Decision Science and Information Systems and Management. The selection includes ten prominent journals, each recognized for its academic contribution and extensive publication history. The longest-running journal in the dataset is Information and Management, covering the period from 1977 to 2025, highlighting its longstanding influence in the field. Other well-established journals, such as MIS Quarterly: Management Information Systems (since 1980) and Decision Support Systems (since 1985), continue to shape research in information systems and decision support technologies. The latest inclusion, Big Data Research, covers 2014 to 2025, reflecting the rising significance of data analytics and AI-driven decision-making in management sciences. The dataset underscores the evolving nature of information systems research, integrating traditional management approaches with cutting-edge technological developments.

Examining the number of published articles, Knowledge-Based Systems remains the most prolific journal in the dataset, with 7059 articles, significantly surpassing others in research output. Decision Support Systems (1184 articles) and Information and Management (976 articles) also demonstrate substantial contributions to the field. On the other hand, International Journal of Information Management (1214 articles) and European Journal of Information Systems (432 articles) maintain strong academic influence despite a comparatively lower volume of publications. The data set provides a comprehensive reference for researchers seeking authoritative sources in MIS, decision science, and related fields, covering both well-established and emerging research topics. The updated coverage until 2025 ensures the inclusion of the most recent research trends, making it a valuable resource for academics and practitioners alike.

Table 1: Selection of Journals

Journal Name	**Category / Subcategory**		**Number of Articles**	**Coverage**
	Business, Management and Accounting	Decision Science		

	Management Information Systems	Information Systems and Management		
International Journal of Information Management	1	1	1214	1986-2025
European Journal of Information Systems	2	2	432	1995-2025
Information and Management	5	5	976	1977-2025
Journal of Strategic Information Systems	6	7	240	1991-2025
Knowledge-Based Systems	8	8	7059	1987-2025
Decision Support Systems	9	9	1184	1985-2025
MIS Quarterly: Management Information Systems	11	13	611	1980-2025
Journal of Management Information Systems	16	20	469	1987-2025
Information Systems Research	19	23	689	1990-2025
Big Data Research	21	28	338	2014-2025

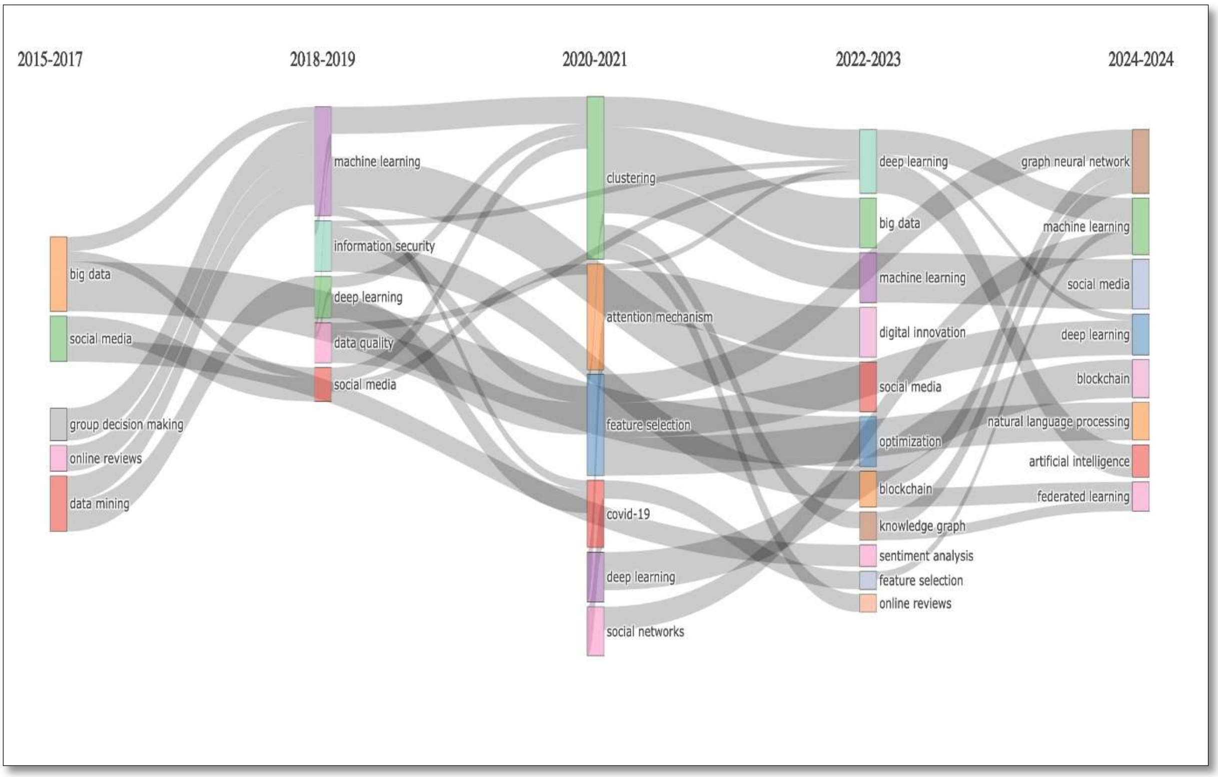
The dataset provides a comprehensive overview of academic publications in the domain of MIS, spanning a decade from 2015 to 2024, and sourced from ten prominent journals. The annual scientific production shows a notable upward trend, with the number of articles increasing from 829 in 2014 to 1,804 in 2022, indicating significant growth in research activity. The most prolific journal, "Knowledge-Based Systems," contributed 6,814 articles, followed by "Decision Support Systems" with 1,307 articles, and "International Journal of Information Management" with 1,165 articles.

3. Findings

3.1. Thematic Evolution of MIS during last decade

Over the past decade, Management Information Systems (MIS) research has undergone a significant transformation, driven by advancements in artificial intelligence, big data analytics, cybersecurity, and digital innovation. The increasing reliance on data-driven decision-making and automation has led to a shift in research focus from traditional data mining and group decision-making toward more sophisticated techniques such as deep learning, blockchain, and federated learning. Figure 1 presents evaluation of Management Information System during last decade below.

Figure – 1 : Thematical Evolution of MIS



From 2015 to 2017, research in Management Information Systems (MIS) focused on data-driven decision-making, with significant emphasis on Big Data, Social Media, and Data Mining. These topics laid the groundwork for analytical advancements, particularly in customer behaviour analysis and business intelligence. Additionally, Group Decision Making and Online Reviews were explored, reflecting the early adoption of technology in business and marketing strategies. This period marked the initial phase of digital transformation, where data became a critical asset in management systems.

Between 2018 and 2019, a shift towards Artificial Intelligence (AI) began, with Machine Learning and Deep Learning emerging as dominant research themes. These technologies facilitated predictive analytics, automation, and enhanced decision-making in business environments. Alongside AI, Information Security gained prominence, indicating growing concerns over data privacy and cybersecurity risks. The importance of Data Quality was also recognized, highlighting the need for reliable and well-structured datasets in MIS applications. Social Media Analytics remained a key area of study, with research expanding into its impact on consumer behaviour and business performance.

In 2020 and 2021, the adoption of AI-driven methodologies expanded further, with Clustering, Attention Mechanisms, and Feature Selection becoming focal points in MIS research. These techniques improved data categorization, recommendation systems, and decision automation. A significant new research trend emerged in response to the COVID-19 pandemic, emphasizing the role of digital tools in crisis management and business continuity. Deep Learning continued to gain momentum, integrating with other technologies to optimize decision-making processes. The study of Social Networks also grew, reflecting their increasing influence on business strategy and market trends.

From 2022 to 2023, MIS research became more diversified, integrating Digital Innovation, Optimization, and Knowledge Graphs. The focus shifted toward enhancing efficiency, automation, and data connectivity in business operations. Blockchain technology gained traction, signaling its potential in securing transactions, decentralizing data storage, and enhancing transparency in digital ecosystems. Sentiment Analysis and Feature Selection remained active research areas, reinforcing the role of AI in understanding consumer behavior and optimizing machine learning models. Social Media remained a key research topic, reflecting its continuous evolution in business intelligence.

In the most recent period from 2024 to 2025, trends in MIS research indicate a strong shift toward advanced AI models and decentralized learning frameworks. Graph Neural Networks (GNNs) and Federated Learning emerged as cutting-edge topics, signifying a transition toward privacy-preserving AI and distributed data processing. Artificial Intelligence (AI), Natural Language Processing (NLP), and Blockchain continue to dominate research, with applications expanding into finance, cybersecurity, and smart automation. Social Media Analysis integrates AI-driven insights, showing its persistent relevance in digital marketing and customer relationship management. The field is now characterized by an increased focus on ethical AI, secure data-sharing mechanisms, and more sophisticated decision-support systems.

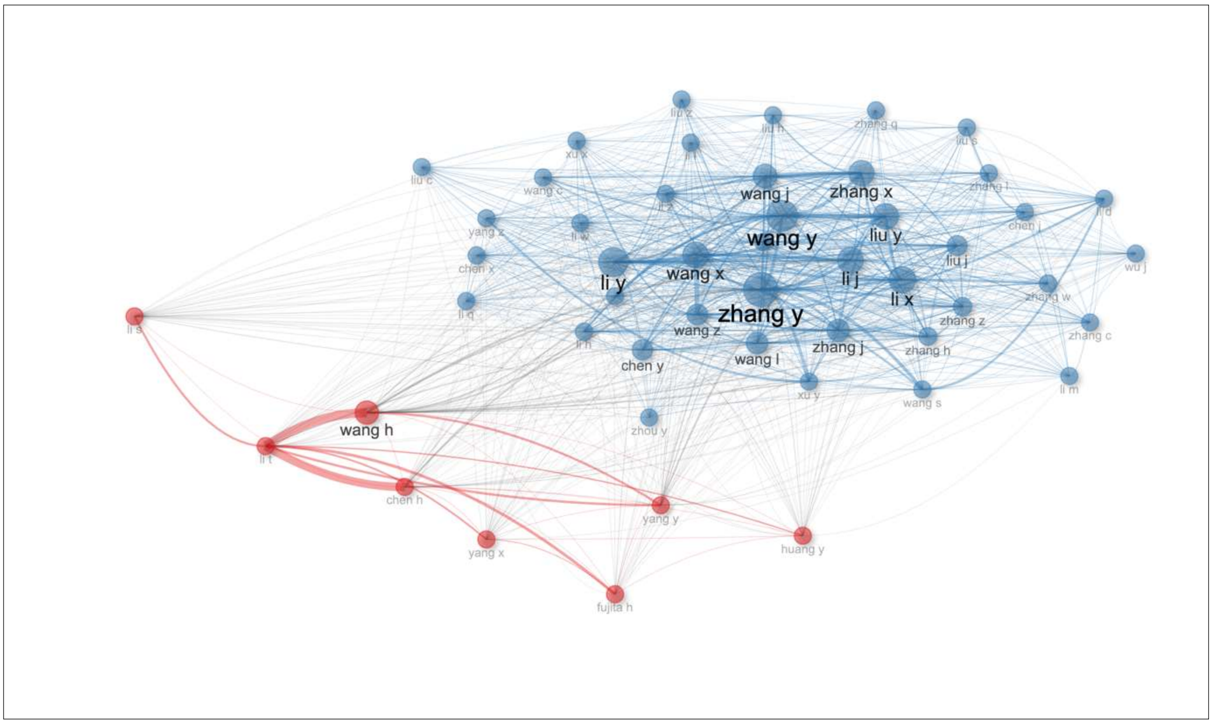
Over the past decade, MIS research has evolved from basic data analytics and decision support systems to AI-driven automation, security enhancements, and decentralized intelligence. The integration of Machine Learning, Blockchain, NLP, and Federated Learning showcases the shift toward more advanced, intelligent, and privacy-conscious management information systems. Future research in MIS is expected to further explore human-AI collaboration, ethical AI frameworks, and innovative applications of emerging technologies.

3.2. Collaborative Perspectives of MIS

3.2.1. Authorship collaboration

The total number of authors contributing to literature in dataset is 16,819. Notably, 408 authors are responsible for single-authored documents, while the dataset comprises 494 single-authored documents in total. This indicates a strong tendency towards collaborative research, further evidenced by the average of 3.78 co-authors per document. Additionally, international collaborations are a significant aspect of this research domain, with 37.08% of the documents involving co-authorships across different countries. Furthermore, the most prolific authors are Zhang. Y., leading at 279 documents, followed by Wang Y with 253 documents, and Li. Y, with 249 documents. Also, in Figure 2, the collaborative relationships among the most prolific authors are presented. Central figures such as Zhang Y., Wang Y., and Li Y. demonstrate extensive co-authorship networks, indicating their prominent roles and strong collaborative ties within the academic community. The distinct clusters, represented in different colours, highlight the existence of sub-communities and key collaboration hubs, with Wang H notably forming a separate, well-connected cluster.

Figure 2: Authorship collaboration

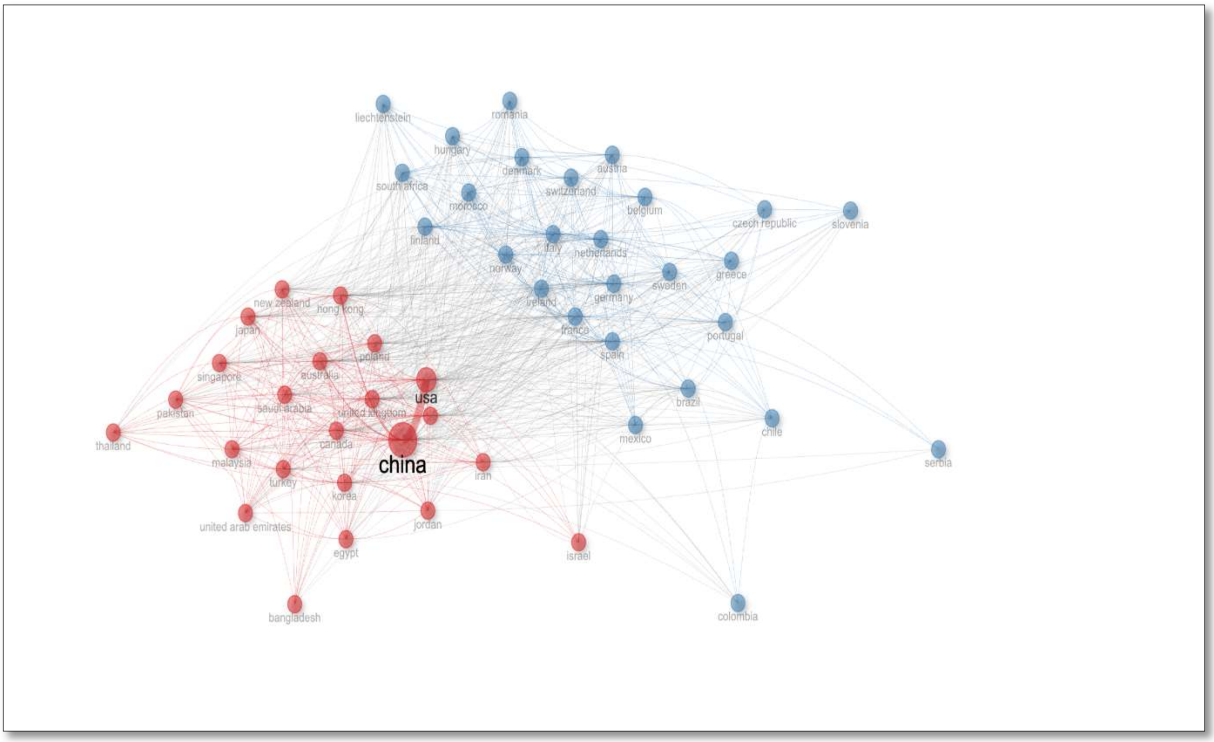


3.2.2. Country collaboration

This network visualization represents international collaborations, with countries grouped into two primary clusters based on their connections in Figure 3. The red cluster, dominated by China and the USA, includes many Asian, Middle Eastern, and Commonwealth nations, indicating strong regional or economic ties. The blue cluster is largely composed of European countries, along with some South American nations, suggesting a distinct collaborative network. The size of the nodes signifies the centrality or importance of a country within the network, with China and the USA being the most prominent hubs in the red cluster, while Germany, France, and other European nations are central in the blue cluster.

Furthermore, the thickness and number of edges (lines) indicate the strength and frequency of collaborations, with some countries serving as bridges between the two clusters through inter-group connections (gray edges). These connections suggest that while the two clusters have distinct internal collaborations, there are cross-cluster interactions, likely representing trade relationships, research partnerships, or diplomatic engagements. The visualization highlights regional collaboration trends and potential geopolitical or economic alliances shaping international networks.

Figure 3: Country collaboration



Furthermore, Table 2 provides an overview of the strongest international collaborations, highlighting key partnerships between countries based on their collaboration frequency. The data reveals that China and the USA emerge as dominant global hubs, engaging in extensive partnerships across various regions. China demonstrates particularly strong ties with Hong

Kong (348), Australia (322), the United Kingdom (273), and Singapore (209), indicating a mix of regional and international collaborations. Similarly, the USA maintains significant connections with Canada (188), Hong Kong (188), Australia (130), Korea (125), and the United Kingdom (125), reflecting its widespread influence in global cooperation.

These trends suggest that geopolitical and economic factors play a crucial role in shaping international collaboration networks. China's strong intra-Asian ties, along with its connections to major Commonwealth countries, underscore its strategic approach to global engagement. Meanwhile, the USA's close relationships with Canada and Asia-Pacific nations highlight its diverse and expansive collaboration strategy. The high frequency of these partnerships indicates the presence of well-established networks, likely driven by academic, technological, and economic exchanges. Overall, the data illustrates how China and the USA act as central nodes in the global collaboration landscape, fostering connections that bridge regional and international boundaries.

Table 2: Countries' Collaboration World Map

From	To	Frequency
CHINA	USA	875
CHINA	HONG KONG	348
CHINA	AUSTRALIA	322
CHINA	UNITED KINGDOM	273
CHINA	SINGAPORE	209
USA	CANADA	188
USA	HONG KONG	188
USA	AUSTRALIA	130
USA	KOREA	125
USA	UNITED KINGDOM	125
CHINA	CANADA	117
CHINA	JAPAN	105
USA	GERMANY	98
USA	SINGAPORE	98

USA	FRANCE	96
USA	INDIA	86
CHINA	FRANCE	79
AUSTRALIA	UNITED KINGDOM	75
CHINA	SAUDI ARABIA	57
USA	NETHERLANDS	56
UNITED KINGDOM	INDIA	52
UNITED KINGDOM	SPAIN	49
CHINA	SPAIN	47
CHINA	KOREA	46
AUSTRALIA	GERMANY	45

3.3. Clusters by Document Coupling

Table 3 presents a detailed analysis of various research clusters based on their frequency, centrality, and impact. Each cluster is defined by a combination of topics and their respective prominence and connectivity within the academic landscape. Cluster 1, which includes deep learning, learning systems, and semantics, shows a high frequency of 4,442 documents and a moderate centrality of 0.021. This cluster has an impact score of 2.21, reflecting its significant influence in these interconnected areas of research.

Cluster 2, focused on social networking (online), information systems, and sales, has the highest frequency with 4,509 documents and a centrality of 0.022. Notably, it boasts the highest impact score of 3.14 among the listed clusters, indicating its substantial influence and importance in the academic community. Cluster 3, which covers classification of information, learning systems, and clustering algorithms, has a lower frequency of 1,161 documents and a centrality of 0.015, but it maintains a respectable impact score of 2.39.

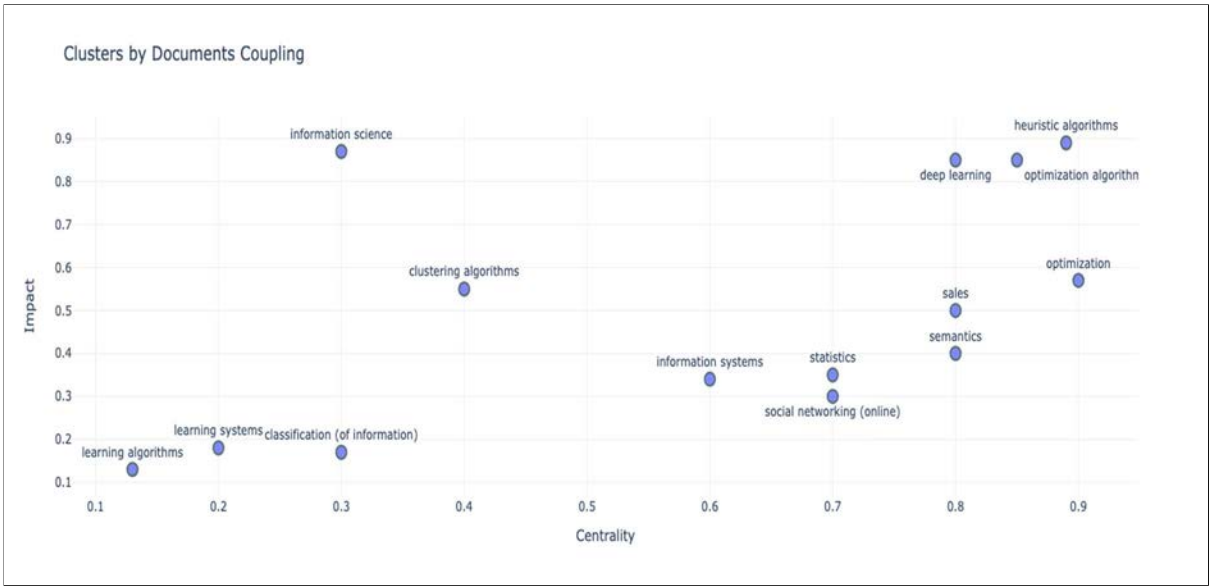
Cluster 4, comprising semantics, social networking (online), and statistics, is smaller with only 265 documents but has a relatively high impact score of 2.57 and a centrality of 0.016. This suggests that despite its size, the cluster is highly impactful. Cluster 5, which includes information systems, social networking (online), and information science, has a frequency of 1,408 documents and a centrality of 0.015, with an impact score of 2.42. Lastly, Cluster 6, focusing on classification of information, learning systems, and learning algorithms, has 469 documents, a centrality of 0.021, and an impact score of 1.78. Cluster 7, which covers optimization, optimization algorithms, and heuristic algorithms, has a frequency of 507 documents, the highest centrality of 0.023, and the highest impact score of 4.85, underscoring its significant role and influence in the field.

Table 3: Clusters and labels for article coupling

Clusters	Labels	Frequency	Centrality	Impact
1	deep learning (85.4%), learning systems (61.2%), semantics (79.2%)	4442	0.021	2.21
2	social networking (online) (66.2%), information systems - (63.5%), sales (71.4%)	4509	0.022	3.14
3	classification (of information) (30.7%), learning systems (18.3%) clustering algorithms (55.9%)	1161	0.015	2.39
4	semantics (8.1%), social networking (online) (4.5%), statistics - (35.6%)	265	0.016	2.57
5	information systems (34%) social networking (online) (16.4%) information science - (87.7%)	1408	0.015	2.42
6	classification (of information) (17.5%), learning systems - (8.5%), learning algorithms - (13.1%)	469	0.021	1.78
7	optimization - (57.9%) optimization algorithms - (85%) heuristic algorithms (89.8%)	507	0.023	4.85

Furthermore, Document coupling facilitates knowledge integration and cross-fertilization across different research areas. Figure 3 illustrates the relationship between document coupling and impact. Clusters like "information science" and "clustering algorithms," which have high impact but moderate centrality, indicate their specialized yet influential nature. In contrast, clusters like "heuristic algorithms" and "optimization algorithms," positioned high on both axes, signify their pivotal role and extensive connectivity within the research landscape, underscoring the influence of document coupling. Additionally, clusters like "social networking (online)" and "information systems" display moderate centrality and impact, acting as important bridging areas.

Figure 3: Network Map for collaborative studies.



When articles are frequently coupled, it suggests they draw on similar foundations or address related problems, encouraging cross-fertilization of ideas. This interconnectedness can lead to the development of more comprehensive and innovative solutions, thereby increasing the scholarly impact of the coupled documents. Notably, clusters like "deep learning," "optimization algorithms," and "social networking (online)" benefit from such integration, leading to their notable impact despite varying degrees of centrality.

4. Discussion

The findings offer substantial contributions to the Management Information Systems (MIS) literature. Firstly, The findings align with Youtie et al. (2013), emphasizing that document coupling serves as a crucial bibliometric measure that enhances the visibility and citation rates of academic papers, thereby increasing their overall impact. This insight is crucial for researchers and institutions aiming to increase their academic influence and recognition.

Additionally, by mapping the thematic clusters within the field, this study provides a comprehensive overview of the evolving research trends and collaborative networks, highlighting key areas of focus and emerging topics in knowledge-based systems. These contributions are particularly relevant as the MIS discipline continues to mature and establish itself as a reference discipline for other fields (Salvaneschi, 2011) . The detailed analysis of collaborative patterns and the identification of prolific authors and international partnerships also provide valuable information for fostering future collaborations and enhancing the global interconnectedness of MIS research.

Furthermore, the study highlights the significant role of collaborative research networks, with international partnerships and interdisciplinary studies contributing to the maturation of MIS as a reference discipline (Zhang, 2013). The findings indicate that AI-driven methodologies, optimization techniques, and decentralized learning frameworks are set to drive the future of MIS research, integrating privacy-preserving technologies and ethical AI considerations. As MIS continues to evolve, future research should further explore the implications of AI on decision-making, digital transformation strategies, and the intersection of MIS with emerging technologies. By mapping out these research trajectories, this study provides valuable insights for scholars, practitioners, and policymakers, helping to shape the next generation of data-driven and intelligent MIS solutions.

5. Conclusion and Recommendations

This study explored the influence of document coupling on the impact and visibility of academic research within the field of Management Information Systems and identified predominant research clusters from 2014 to 2024. Employing a detailed bibliometric analysis of ten prominent journals, significant trends and patterns in research activity, authorship, and collaboration were identified.

The findings of this study have significant practical implications for academics, industry practitioners, policymakers, and technology developers operating in the field of Management Information Systems (MIS). The evolution of research themes over the past decade indicates a growing reliance on AI-driven decision-making, digital innovation, and data security, which businesses and organizations must integrate into their strategic planning and operational frameworks. The increasing role of big data analytics, machine learning, and blockchain technologies suggests that organizations should prioritize data governance, cybersecurity measures, and AI-driven automation to enhance efficiency and competitiveness. Practitioners can leverage insights from this study to identify emerging MIS trends and implement state-of-the-art technologies that optimize decision-making, streamline business operations, and enhance customer experiences.

From an academic perspective, the study emphasizes the importance of interdisciplinary collaboration and the role of document coupling in amplifying research visibility and impact. Universities and research institutions should encourage collaborative research projects and international partnerships to contribute to high-impact publications and influence the trajectory of MIS research. Additionally, policymakers and regulatory bodies must recognize the growing importance of AI, federated learning, and decentralized technologies, ensuring that data privacy, transparency, and digital ethics remain at the forefront of emerging MIS applications. By integrating these insights into policy frameworks, governments and industry regulators can foster responsible AI adoption, support digital transformation initiatives, and bridge the digital divide in different sectors. Ultimately, the findings serve as a guiding reference for decision-makers across academia, industry, and governance in shaping the future of MIS-driven innovation and strategic planning.

Despite its contributions, this study has several limitations. The reliance on data from selected journals, while comprehensive, may not capture the full scope of research activity within the broader field of knowledge-based systems. Future research could expand the dataset to include a wider array of journals and other types of publications, such as conference proceedings and book chapters, to provide a more exhaustive analysis. Additionally, the study's time frame, although extensive, is limited to a decade. Longitudinal studies extending beyond this period could offer deeper insights into the historical evolution and future trajectories of research trends in knowledge-based systems.

Another limitation is the focus on bibliometric measures such as document coupling and citation analysis. While these are valuable indicators of academic impact, incorporating qualitative assessments of research contributions and practical applications could provide a more detailed understanding of the field's influence. Future research should also explore the implications of emerging technologies and methodologies on document clustering and information retrieval. Investigating the impact of artificial intelligence and machine learning advancements on these processes could unveil new opportunities for enhancing knowledge organization and retrieval efficiency.

References

Aria, M. & Cuccurullo, C. (2017) bibliometrix: An R-tool for comprehensive science mapping analysis, Journal of Informetrics, 11(4), 959-975, Elsevier.

Baskerville, R.L., & Myers, M.D. (2002). Information Systems as a Reference Discipline. MIS Q., 26, 1-14.

Benbasat, I., & Zmud, R.W. (2003). The Identity Crisis Within the IS Discipline: Defining and Communicating the Discipline's Core Properties. MIS Q., 27, 183-194.

Bernroider, E. W., Pilkington, A., & Córdoba, J. R. (2013). Research in information systems: a study of diversity and inter-disciplinary discourse in the AIS basket journals between 1995 and 2011. *Journal of Information Technology*, *28*(1), 74-89.

Camarinha-Matos, L. M., & Afsarmanesh, H. (2004, August). The emerging discipline of collaborative networks. In *Working Conference on Virtual Enterprises* (pp. 3-16). Boston, MA: Springer US.

Cheng, X., Miao, D., Wang, C., & Cao, L. (2013). Coupled term-term relation analysis for document clustering. *The 2013 International Joint Conference on Neural Networks (IJCNN)*, 1-8.

Coccia, M., & Wang, L. (2016). Evolution and convergence of the patterns of international scientific collaboration. *Proceedings of the National Academy of Sciences*, *113*(8), 2057-2061.

Dickson, G. W. (1968). Management information-decision systems: A new era ahead?. *Business Horizons*, *11*(6), 17-26.

Ferreira, K.A., Flávio, L.A., & Rodrigues, L.F. (2018). Postponement: bibliometric analysis and systematic review of the literature. *International Journal of Logistics Systems and Management, 30*, 69-94.

Garro Abarca, V.M., Palos-Sánchez, P.R., & Rus-Arias, E. (2020). Working in Virtual Teams: A Systematic Literature Review and a Bibliometric Analysis. *IEEE Access, 8*, 168923-168940.

Grover, V., Gokhale, R., Lim, J., & Ayyagari, R. (2006). About reference disciplines and reference differences: A critique of Wade et al. *Journal of the Association for Information Systems*, *7*(5), 11.

Jarneving, B. (2007). Bibliographic coupling and its application to research-front and other core documents. *Journal of informetrics*, *1*(4), 287-307.

Lazarides, M.K., Lazaridou, I., & Papanas, N. (2023). Bibliometric Analysis: Bridging Informatics With Science. *The international journal of lower extremity wounds*, 15347346231153538 .

Machnik, L. (2004). Documents Clustering techniques. *Ann. UMCS Informatica, 2*, 401-411.,

Mandloi, R., Sawant, K., & Vyas, S. (2021). Literature Survey of Various Techniques of Documents Clustering. *2021 International Conference on Advances in Technology, Management & Education (ICATME)*, 1-3.

Moral-Muñoz, J. A., López-Herrera, A. G., Herrera-Viedma, E., & Cobo, M. J. (2019). Science mapping analysis software tools: A review. *Springer handbook of science and technology indicators*, 159-185.

Nambisan, S. (2003). Information Systems as a Reference Discipline for New Product Development. *MIS Quarterly*, *27*(1), 1–18. https://doi.org/10.2307/30036517

Salvaneschi, P. (2011, September). The evolution of Information Systems a case study on document management. In 2011 27th IEEE International Conference on Software Maintenance (ICSM) (pp. 428-437). IEEE.

Vessey, I., Ramesh, V., & Glass, R. L. (2002). Research in information systems: An empirical study of diversity in the discipline and its journals. *Journal of management information systems*, *19*(2), 129-174.

Youtie, J., Kay, L., & Melkers, J. (2013). Bibliographic coupling and network analysis to assess knowledge coalescence in a research center environment. *Research Evaluation*, *22*(3), 145-156.

Zhang X (Julia). The Evolution of Management Information Systems: A Literature Review. Journal of Integrated Design and Process Science. 2013;17(2):59-88. doi:10.3233/jid-2013-0009

Paper #62

Title: Analysis of Customer Reviews with Text Analytics Techniques in the Tourism Sector: Pandemic Effect

Author(s): Şaheste Akpınar, Dilek Sürmeli and Halil İbrahim Cebeci

Abstract:
This paper analyzes over 120,000 hotel reviews from Antalya, Turkey, to evaluate shifts in customer perceptions before and after the COVID-19 pandemic. Using text mining, topic modeling, and sentiment analysis, the study finds that while hotel personnel and facilities remain central concerns, hygiene becomes significantly more emphasized post-pandemic.

Keywords: Text Analytics, Sentiment Analysis, Tourism, COVID-19, Customer Reviews

Paper #31

Title: Nagorno-Karabakh Crisis: An Evaluation from the Perspective of Social Media Analytics

Author(s): Burak Arslan and Emrah Aydemir (Sakarya University)

Abstract:
This study uses text mining and topic modeling to analyze over 600,000 social media posts shared during the 2020 Nagorno-Karabakh war. It identifies themes such as information sharing, celebration, and hate speech, showing how public sentiment evolves during a prolonged conflict. The results emphasize social media's dual role in communication and polarization.

Keywords: Text Mining, Social Media, Topic Modeling, Nagorno-Karabakh

Paper #36

Title: A Methodological Framework for Lean Intrapreneurship: Challenges, Drivers, and a Case Study in Digital Banking

Author(s): Çağlar Şimşek and Fatih Çallı (Sakarya University)

Abstract:
This paper presents a case study on MYYCAR, a digital banking initiative, to explore lean intrapreneurship within financial institutions. It outlines a five-stage framework based on design thinking and lean startup principles, emphasizing MVP development, adaptive governance, and user feedback. The study highlights how intrapreneurs can drive innovation in highly regulated environments.

Keywords: Lean Intrapreneurship, Digital Banking, Design Thinking, Innovation, Financial Institutions

Paper #34

Title: The Impact of National Institutional Innovation Differences on ICT-Enabled Export

Author(s): Mesut Mutlu, Nihan Yıldırım, and Derya Gültekin (İstanbul Technical University)

Abstract:
This paper investigates how differences in institutional innovation between countries affect ICT-enabled service exports. Using a bilateral gravity trade model and institutional data from the Global Innovation Index (GII), the study shows that greater disparities in institutional quality—such as governance and regulatory efficiency—positively impact export volumes. The findings provide policymakers with insights to strengthen institutional frameworks that support the digital economy.

Keywords: ICT-Enabled Services, Institutional Innovation, Global Innovation Index, Digital Trade, Gravity Model

Paper #44

Title: A Review on the Legal Nature of Artificially Intelligent Beings

Author: Doğa Ekrem Doğancı and Merve Özaydın

Abstract:
This paper explores the legal classification of AI systems, comparing low-autonomy and high-autonomy entities through various doctrinal perspectives. It evaluates concepts such as property, slave, servant, and electronic personality under Turkish and international law. The study concludes that granting limited legal personhood to advanced AI could address emerging legal challenges and enhance accountability frameworks.

Keywords: Artificial Intelligence, Legal Personality, Personhood, Turkish Law, Ethics and Law

Paper #41

Title: Analysis of the Relationship Between Digital Literacy and Digital Citizenship in High School Students

Author(s): İlkay Ersoy, Yalçın Yayla and Dr. Öğr. Üyesi Tuğba Koç

Abstract:
This study examines the correlation between digital literacy and digital citizenship among 305 Turkish high school students. Using quantitative methods and structural equation modeling, the research finds a strong positive relationship between the two concepts. The paper highlights the importance of integrating digital citizenship education into school curricula to foster responsible digital behavior.

Keywords: Digital Literacy, Digital Citizenship, High School Students, Education, Digital Competence

Skin Cancer Detection with Deep Learning-Based Object Detection Models

Sarah Almusawi[1*], İsmail Hakkı Cedimoğlu[1], Merve Şişci[2]

[1]*Information Systems Engineering Department, Sakarya University, Sakarya, Türkiye*

[2]*Industry Engineering Department, Kütahya Dumlupınar University, Kütahya, Türkiye*

*Corresponding author E-mail: almusawis706@gmail.com, Sakarya University, Faculty of Computer and Information Sciences, Information Systems Engineering Department, 54050, Serdivan-SAKARYA/TÜRKİYE

Abstract

Skin cancer, one of the most life-threatening cancers, can be effectively treated if diagnosed early, thereby reducing mortality rate. This study evaluates the effectiveness of YOLOv8 and YOLOv11 models for skin cancer detection from dermoscopic images. In the study, deep learning-based object detection techniques were used to classify benign and malignant skin lesions with high accuracy. A dataset containing a total of 3,297 images was used in the study and was divided into training, validation and test sets. The models were trained using Python and PyTorch with GPU support. A total of 10 different YOLO models were developed and precision, recall, F1-score, mAP@0.5, mAP@0.5:0.95 and evaluated with MITF performance metrics. YOLOv11s, %77.18 precision, %80.25 recall, %78.69 F1-score, and 6.8 it was the most balanced model with ms/image extraction time. YOLOv8x was determined as the model with the lowest accuracy and the highest computational cost. In this study reveals that YOLO-based models have great potential in medical imaging applications for real-time skin cancer detection. With its particularly lightweight structure and high accuracy, the YOLOv11s model stands out as a suitable option for use in mobile and clinical devices.

Keywords: Skin cancer detection, Object detection, Deep learning, YOLOv8, YOLOv11

1. Introduction

Skin cancer is one of the most common types of cancer worldwide and early detection is vital (American Cancer Society, 2023). Traditional diagnostic methods often face major challenges, such as traditional dependence on physician examination and biopsy and other diagnostic methods, long procedure times, and high treatment costs. These difficulties reduce the effectiveness of doctors in early diagnosis (Smith et al. 2022). Artificial intelligence and deep learning-based techniques have significantly advanced the field of medical image analysis. These techniques have played a crucial role in enabling earlier and more precise disease detection, thereby improving diagnostic accuracy and patient outcomes (Jones and Brown, 2021).

Object detection models belonging to the YOLO (You Only Look Once) family, developed in recent years, stand out with their real-time and high-precision analysis capabilities (Redmon et al. 2016). This study aims to evaluate different approaches using YOLOv8 and YOLOv11 models for skin cancer detection (Ultralytics, 2023). The advanced architecture of YOLOv8 and YOLOv11 has improved object detection performance and increased speed while maintaining high accuracy (Zhang et al. 2023).

The aim of this study is to investigate the effectiveness of YOLO models in skin cancer detection and to determine which version of these models provides higher success (Li et al. 2022). Recent studies have focused on evaluating the performance of different YOLO versions based on their accuracy, precision, and recall, aiming to identify the most suitable model. (Wang and Lee, 2021). The findings provide important implications for the future of AI-supported medical image analysis applications (Patel et al. 2023).

The rest of the study is organized as follows. In Chapter 2, studies on skin cancer detection are reviewed. In Chapter 3, information is given about the deep learning-based YOLO algorithms used in this study for skin cancer detection from images. In Section 4, the methodology and application applied in the study are explained. In Section 5, experimental results are given. In Section 6, conclusions are given.

2. Literature Research

Nie et al. (2019) compared YOLOv2 and YOLOv3 models with R-CNN and SSD. While the YOLOv2 model achieved 83% accuracy, the YOLOv3 model achieved 77% accuracy. The study aimed to develop a system that can be used in mobile applications and 200 images from the ISIC dataset were used.

Sutaji and Yildiz (2023) analyzed the performance of small, medium and large layers of YOLOv8. The large layer mAP value was measured as 79.6%. The study aimed to optimize the accuracy in skin cancer detection and used the HAM10000 dataset.

Aishwarya et al. (2023) applied a fusion strategy by testing YOLOv3-tiny and YOLOv8s models. YOLOv8s accuracy was 93.4% while fusion result achieved 94.3% accuracy. The study used ISIC 2020 dataset.

Tchema et al. (2024) detected and classified skin lesions using YOLOv7 model. The average accuracy was measured as 89.65%, sensitivity as 85% and specificity as 91.90%. MED-NODE dataset was used.

Datta et al. (2023) tested the YOLOv7-tiny model on low-cost devices. The mAP value was measured as 82.1%. 2750 images from the ISIC 2017 dataset were used in the study.

Rusydiyah et al. (2023) tested different versions of YOLOv5 on an Android-based skin cancer detection application. The YOLOv5l model achieved 84.4% mAP accuracy, while the

YOLOv5x model achieved 89.0% accuracy. The study was conducted on eight skin disease categories using the ISIC 2019 dataset.

Similarly, Albahli et al. (2022) aimed to accurately classify and segment skin cancer lesions by developing a YOLOv4-DarkNet based model. With the CSPDarkNet-53 model used in the study, the Jaccard index was reported as 98% and the sensitivity was reported as 93.2%. In the study, the effectiveness of the model was tested using ISIC 2016 and ISIC 2018 data sets.

Hum et al. (2022) developed a deep learning model based on AlexNet and used it in skin cancer diagnosis. Feature extraction was performed with CNN and classification was performed with ECOC SVM. The model achieved 95.1% accuracy for squamous cell carcinoma and 98.9% sensitivity for actinic keratosis. RGB skin lesion images collected from the internet were used for training.

Malo et al. (2022) developed a system using Keras and TensorFlow. VGG-16 model was optimized with transfer learning method and 87.6% accuracy rate was achieved. ISIC dataset was used.

Tabrizchi et al. (2023) achieved 93% AUC accuracy by improving the VGG-16 architecture. The model outperformed models such as ResNet50 and AlexNet. 33,126 images were used in the study.

Tuncer et al. (2024) developed the TurkerNet model with fewer training parameters. The model achieved 92.12% testing accuracy. Kaggle dataset was used.

Aishwarya et al. (2023) conducted skin cancer classification using YOLOv3 and YOLOv4. YOLOv3 achieved an mAP of 88.03%, while YOLOv4 achieved an mAP of 86.52%. The ISIC dataset was used.

Hasna et al. (2021) used YOLOv3 and CNN for real-time skin cancer detection. Static accuracy was measured as 96% and real-time accuracy as 80%. HAM10000 dataset was used.

Gouda et al. (2022) detected skin cancer by improving image quality with ESRGAN. InceptionV3 model gave the best result with an accuracy rate of 85.7%. ISIC 2018 dataset was used.

AlSadhan et al. (2024) compared YOLOv3, YOLOv4, YOLOv5 and YOLOv7 models. YOLOv7 showed the best performance with 75.4% mAP and 86.3% IoU. ISIC 2017 dataset was used.

Nersisson et al. (2021) achieved 94% accuracy by combining YOLOv2 with traditional features. ISBI Melanoma dataset was used.

The aimed to detect malignant skin cancer from dermatoscopic images with a MobileNetV2 and SVM-based method by Demir (2021). In the dataset consisting of 3,297 images, the accuracy rate of the model was 88.35% and was increased by 2.31% with feature selection. The method is suitable for clinical use with low computational cost. In the future, it is aimed to develop the model and adapt it to mobile platforms.

Riyadi et al. (2024) conducted a study on skin cancer detection and classification using YOLOv8n algorithm. The model was trained using 4289 images from ISIC 2019 dataset. YOLOv8n achieved 100% accuracy, especially in the basal cell carcinoma and vascular lesion categories, with 93.5% accuracy, 93.7% sensitivity, and 93.5% F1 score. The study aimed to provide an effective method for rapid and sensitive skin cancer detection.

Ćirković et al. (2024) studied a dataset of 3000 images using the YOLOv8 algorithm and achieved an overall accuracy rate of 78.2%. The study aimed to provide dermatologists with a preliminary screening tool.

3. Algorithms Used

YOLO, short for "You Only Look Once", is a real-time object detection algorithm first introduced by Joseph Redmon in 2016 (Redmon et al. 2016). It is an advanced object detection algorithm that provides fast and efficient real-time detection thougha single pass through of a unified neural network (Albahar, 2019; Redmon et al. 2016). Unlike traditional methods that divide an the image into sub-regions, YOLO processes the image as a holistic entity, simplifying the detection process. This process involves using bounding boxes to identify and classify the target object (Riyadi et al. 2024; Redmon et al. 2016). The YOLO family has evolved greatly in recent years (Soni, and Rai, 2024) and this makes it one of the most powerful algorithms for real-time object detection in terms of speed and accuracy. In this study, the latest versions of the YOLO family, YOLOv8 and YOLOv11, were used.

3.1 YOLOv8

YOLOv8 is one of the most advanced models developed in the field of object detection. It was developed by Ultralytics and released in January 2023 (Reis et al. 2023). It introduces significant improvements over previous versions of the YOLO series, particularly YOLOv5. It supports a borad range of computer vision tasks, including object detection, segmentation, pose estimation, tracking and classification, while offering superior speed and accuracy in real-time applications and edge computing environments (Reis et al. 2023; Terven et al. 2023).

Unlike its predecessors, which rely on anchor-based models, YOLOv8 is anchor-free, introducing a different approach from previous version (Ragab et al. 2024; Soni and Rai, 2024; Farooq et al. 2024). This eliminates the need for predefined anchor boxes, as YOLOv8 divides the image into a grid of cells, allowing each cell to accurately predict objects. This approach facilitates faster detection and reduces computational complexity (Farooq et al. 2024). Additionally, YOLOv8 improves detection accuracy by using Feature Pyramid Network (FPN) and Path Aggregation Network (PAN). FPN, improves object detection of objects for different sizes and shapes by reducing spatial resolution and increasing feature extraction capabilities. While PAN improves the passage of information between the different layers of the network, which helps to improve detection and increase the detection accuracy of objects (Reis et al. 2023).

YOLOv8 is available in five different editions to suit different hardware needs. YOLOv8n (Nano) is ideal for low-resource devices. YOLOv8s (Small) provides a good balance between performance and model size. YOLOv8m (Medium) offers higher accuracy but increases computational requirements. YOLOv8l (Large) and YOLOv8x (Extra-Large) are the most advanced versions, offering the highest accuracy but requiring large processing power (Terven et al. 2023).

Additionally, to improve training efficiency, YOLOv8 uses hybrid precision training, combining 16-bit and 32-bit floating point, which speeds up the model training process while maintaining high accuracy. It can also be used for various technologies due to its low memory consumption, such as medical imaging, autonomous driving, and smart safety systems (Hussain, 2024).

With these advancements, YOLOv8 has emerged as one of the most advanced object detection models today, integrating high computational efficiency, superior accuracy, and fast execution, and is well-suited for meeting even the most complex requirements of AI-based applications.

3.2.YOLOv11

YOLO11 is the latest addition to the YOLO family, introduced by Ultralytics in 2024 (Jocher et al. 2023). YOLOv11, It emerges as an important innovation in the field of real-time object detection. This model building upon previous YOLO versions and is equipped with architectural and functional improvements. Notably, components such as the C3k2 block and the C2PSA module play critical roles in improving the performance of the model. These innovations contribute to YOLOv11 achieving higher accuracy and efficiency in various computer vision tasks such as object detection, instance segmentation, and pose estimation (Khanam, and Hussain, 2024). This version builds on the strengths of previous versions, offering innovative improvements, particularly in feature extraction and training techniques, and achieves 95.0% accuracy (Sapkota et al. 2024). YOLOv11's architecture is equipped with advanced feature extraction techniques and optimized computational methods. In this way, it is aimed that the model will provide higher accuracy and speed in different computer vision tasks. In particular, components such as C3k2 and C2PSA provide significant contributions to improving the performance of the model (Jegham et al. 2024; Khanam, and Hussain, 2024).

In conclusion, YOLOv11 can be considered as an important step in the field of real-time object detection and segmentation. Its advanced architecture and success in application areas make it a preferred model in computer vision projects.

4. Method

To achieve high-accuracy classification of skin cancer images in the study, a four-step methodology was implemented, consisting of data collection, data preparation, model development and data evaluation, as illustrated in Figure 1.

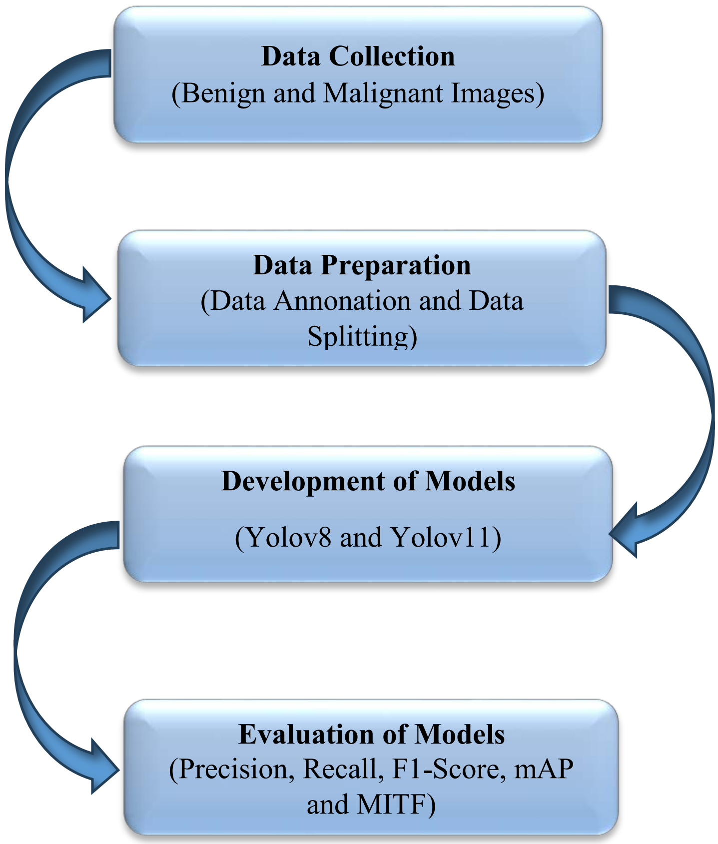


Figure 1. Methodology of the study

4.1.Data Collection

This dataset contains a balanced collection of images containing benign and malignant skin moles. This study was conducted to support skin cancer detection research and model development of predictive models. In this study, we used the Kaggle public dataset. The dataset consists of two main folders: test and train. The test folder comprises 300 benign and 360 malignant images, whereas the training folder consists of 1,440 benign and 1,197 malignant images. All images in this dataset, which contains 2,297 images in total, are 224x244 pixels in size, providing a standard resolution for use in deep learning applications. Sample images for benign and malignant images in the dataset are shown in Figure 2.

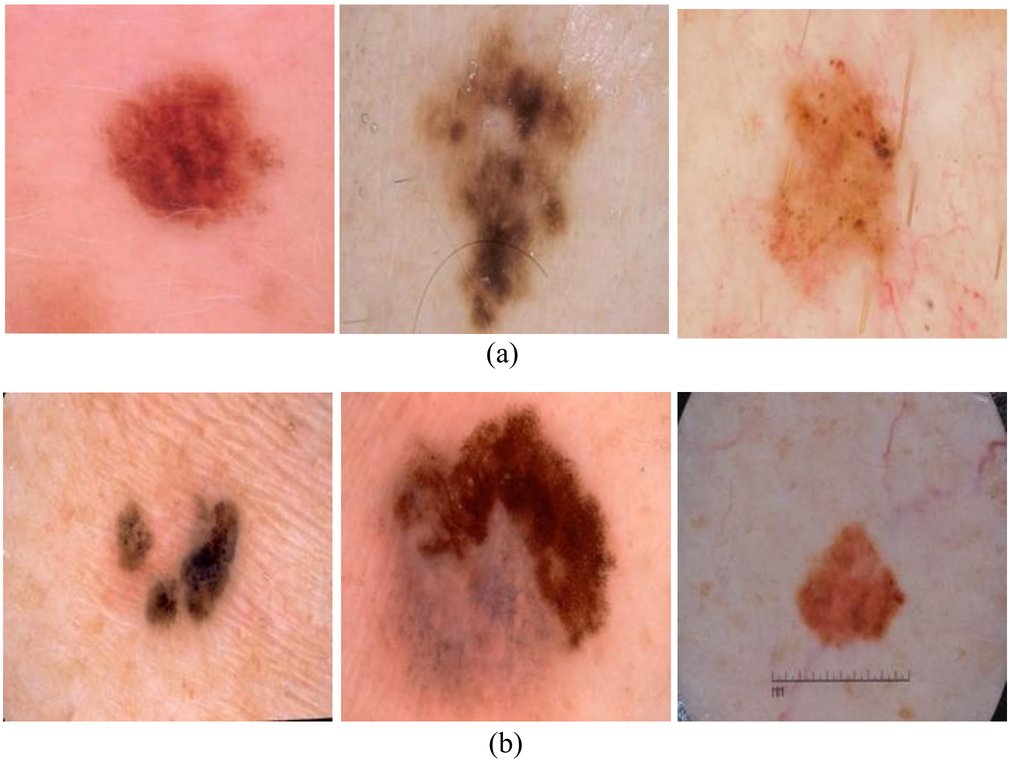


Figure 2. Sample images from the dataset used to detect Skin Cancer (a) benign, (b) malignant

4.2. Data Preparation

The data preparation phase was carried out in two steps: data annotation and data splitting. LabelImg software, an open source tool, was used to label images as benign and malignant. After the data annotation step, 660 images were reserved for testing in the dataset consisting of a total of 3297 images. Of the remaining 2637 images, 70% were used for training and 30% for validation. Data regarding the number of benign and malignant images in the training, validation and test data sets are presented in Table 1.

Table 1. Details of datasets after data splitting

Class	Training Dataset	Validation Dataset	Test Dataset	Total
Malignant	838	359	300	1497
Benign	1008	432	360	1800
Total	1846	791	660	3297

4.3. Development of Models

In the study, during the development phase of skin cancer detection models, 10 different models were developed using YOLOv8n, YOLOv8s, YOLOv8m, YOLOv8l, YOLOv8x, YOLOv11n, YOLOv11s, YOLOv11m, YOLOv11l and YOLOv11x algorithms. The number of layers and parameter numbers of the models are shown in Table 2. While the YOLOv11x model has the highest layer count with 631 layers, the YOLOv8x model has the highest parameter count with 68,154,534 parameters.

Table 2. Number of layers and parameters of YOLOv8 and YOLOv11 models

Model	layers	parameters
YOLOv8n	225	3,011,238
YOLOv8s	225	11,136,374
YOLOv8m	295	25,857,478
YOLOv8l	365	43,631,382
YOLOv8x	365	68,154,534
YOLOv11n	319	2,590,230
YOLOv11s	319	9,428,566
YOLOv11m	409	20,054,550
YOLOv11l	631	25,312,022
YOLOv11x	631	56,876,086

During the training and testing of all models, Python 3.12.4 and Pytorch2.3.1 were used as the programming language, while CUDA12.5 and CUDNN9.2 were utilized on a Windows 10 operating systems. The hardware used in the experimental environment consists of a 12th Generation Intel(R) Core(TM) i7-12700H 2.30 GHz processor and an NVIDIA GeForce RTX 3060 GPU graphics card along with 16 GB of RAM. Training parameters and values of the models are given in Table 3. During training of the models, epoch size was determined as 300 and batch size as 8. The automatic optimizer in the Ultralytics library was used to determine the values of various hyperparameters of the models. The optimization algorithm by the automatic optimizer was determined as the AdamW optimization algorithm (Loshchilov and

Hutter, 2017). On the other hand, the initial learning rate is set to 0.001667 and the momentum is set to 0.9.

Table 3. Training parameters and values of the developed models

Parameter	Value	Parameter	Value
Epoch	300	Patience	100
Batch size	8	Workers	8
Momentum	0.9	Optimizer	AdamW
Input image size	224x224	Weight decay	0.0005
Warmup epochs	3	Initial learning rate	0.001667
Warmup momentum	0.8	Final learning rate	0.01
Warmup bias learning rate	0.1		

In order to prevent the models from overfitting due to excessive number of periods, the Early Stopping (Prechelt, 2002) method was applied during training. In this method, model precision is calculated on the validation data at the end of each period, If there is no increase in precision value during a specified period, the training is terminated (Santos et al. 2022). In this study, the number of this period, called patience, was selected as 100. In this way, YOLOv8n, YOLOv8s, YOLOv8m, YOLOv8l, YOLOv8x, YOLOv11n, YOLOv11s, YOLOv11m, YOLOv11l ve YOLOv11x models completed 300, 284, 295, 139, 194, 281, 295, 300, 300 and 300 epochs, respectively. Training of the models took 4.979, 5.649, 9.002, 8.752, 74.814, 4.445, 5.155, 9.187, 14.359 and 141.770 hours, respectively.

4.4. Evaluation of Models

In evaluating the performance of the models developed using 5 different versions of the YOLOv8 and YOLOv11 algorithms on the validation data set and the test data set, precision, recall, F1-Score, which are widely used in the evaluation of object detection models, mAP@0.5, mAP@0.5:0.95 and Mean Inference Time per Frame (MITF) performance metrics were used. The formulations used in calculating the precision, recall and F1-Score performance metric values are presented in Equations 1-3. Here, TP represents the number of positive samples correctly classified as positive, FP represents the number of negative samples falsely classified as positive, and FN represents the number of positive samples falsely classified as negative.

$$Precision = \frac{TP}{TP+FP} \tag{1}$$

$$Recall = \frac{TP}{TP+FN} \tag{2}$$

$$F1 - Score = \frac{2*Pecision*Recall}{Precision+Recall} \tag{3}$$

The Mean Average Precision (mAP) performance criterion is obtained by calculating the average of the average precision (AP) (Equation 4) value obtained for a single class by calculating the area under the precision-recall (PR) curve for all classes in Equation 5. Here N represents the total number of classes in the dataset.

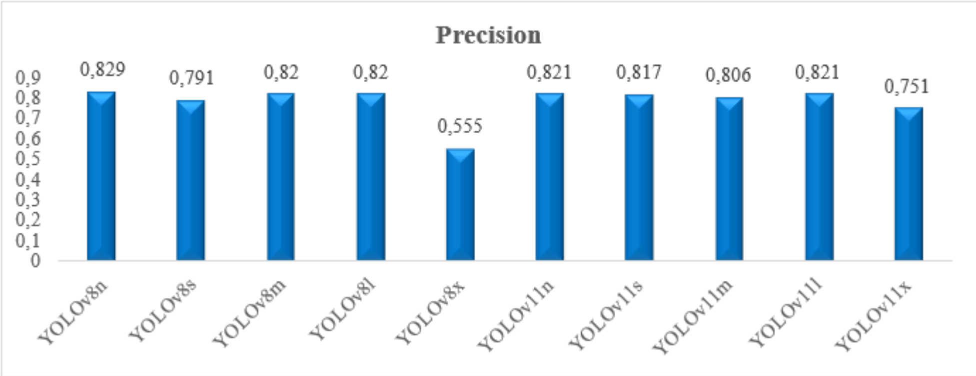
$$AP = \int_0^1 Precision(Recall)d(Recall) \tag{4}$$

$$mAP = \frac{1}{N}\sum_{k=1}^{N} = AP_k \tag{5}$$

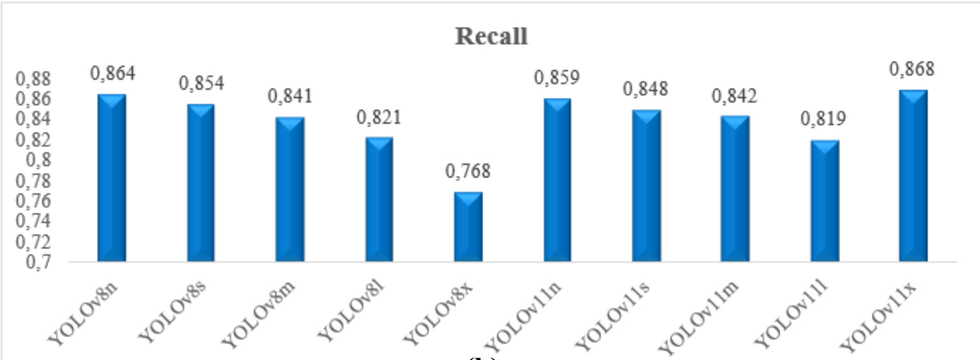
Finally, the MITF performance metric is the inference time taken by the classification model on a single image.

5. Experimental Results

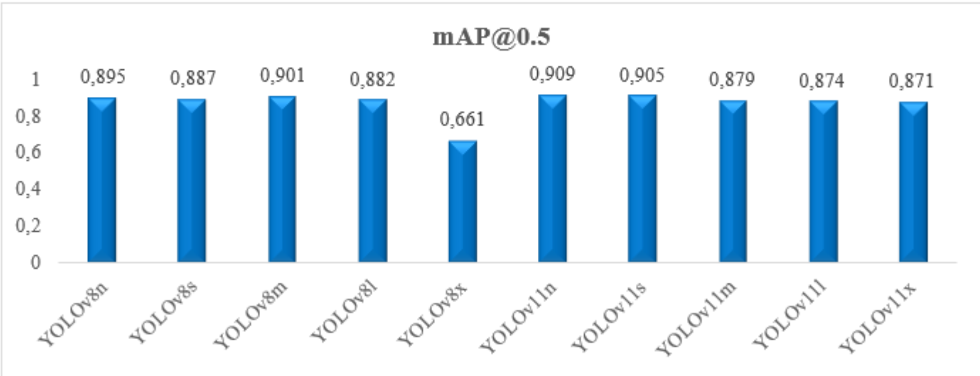
In this section, skin cancer object detection results for different versions of YOLO models are presented. The ten different YOLO-based classifier models developed in the study were trained on the same training dataset, and their performances were evaluated using the test dataset. The performance metric values calculated on the validation dataset during training are presented comparatively in Figure 3. Figure 3(a) illustrates precision values of the models, Figure 3(b) present the recall values, Figure 3(c) shows the mAP@0.5 values, and Figure 3(d) displays the mAP@0.5:0.95 values. When the graphs are examined, it is seen that the YOLOv8n algorithm has the highest precision value with a value of 0.829 and the YOLOv8x model has the lowest precision value with a value of 0.555. When the values are analyzed in terms of recall values, it is understood that the model with the highest performance is the YOLOv11x model with the value of 0.868, and the model with the lowest performance is the YOLOv8x model with the value of 0.768. In the mAP@0.5 performance measurement, the highest and lowest values belong to the YOLOv11n and YOLOv8x models with values of 0.909 and 0.661, respectively. Finally, in terms of mAP@0.5 performance criterion, YOLOv8s model gave the highest value with a value of 0.789, and YOLOv8x model gave the lowest value with a value of 0.414.


Precision
0,9
0,8
0,7
0,6
0,5
0,4
0,3
0,2
0,1
0
0,829
0,791
0,82
0,82
0,555
0,821
0,817
0,806
0,821
0,751
YOLOv8n
YOLOv8s
YOLOv8m
YOLOv8l
YOLOv8x
YOLOv11n
YOLOv11s
YOLOv11m
YOLOv11l
YOLOv11x

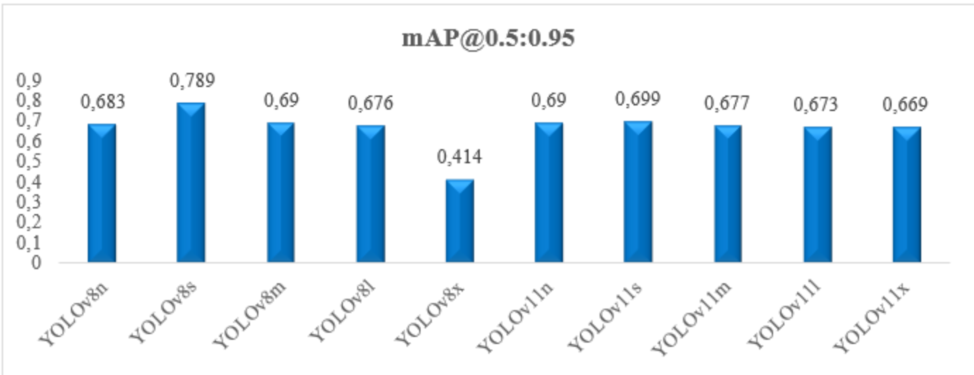
(a)


Recall
0,88
0,86
0,84
0,82
0,8
0,78
0,76
0,74
0,72
0,7
0,864
0,854
0,841
0,821
0,768
0,859
0,848
0,842
0,819
0,868
YOLOv8n
YOLOv8s
YOLOv8m
YOLOv8l
YOLOv8x
YOLOv11n
YOLOv11s
YOLOv11m
YOLOv11l
YOLOv11x

(b)


mAP@0.5
1
0,8
0,6
0,4
0,2
0
0,895
0,887
0,901
0,882
0,661
0,909
0,905
0,879
0,874
0,871
YOLOv8n
YOLOv8s
YOLOv8m
YOLOv8l
YOLOv8x
YOLOv11n
YOLOv11s
YOLOv11m
YOLOv11l
YOLOv11x

(c)


mAP@0.5:0.95
0,9
0,8
0,7
0,6
0,5
0,4
0,3
0,2
0,1
0
0,683
0,789
0,69
0,676
0,414
0,69
0,699
0,677
0,673
0,669
YOLOv8n
YOLOv8s
YOLOv8m
YOLOv8l
YOLOv8x
YOLOv11n
YOLOv11s
YOLOv11m
YOLOv11l
YOLOv11x

(d)

Figure 3. Performance metric values of the models on the validation dataset (a) Precision, (b) Recall, (c) mAP@0.5, (d) mAP@0.5:0.95

For all models, loss function plots on validation sets are presented in Figure 4.

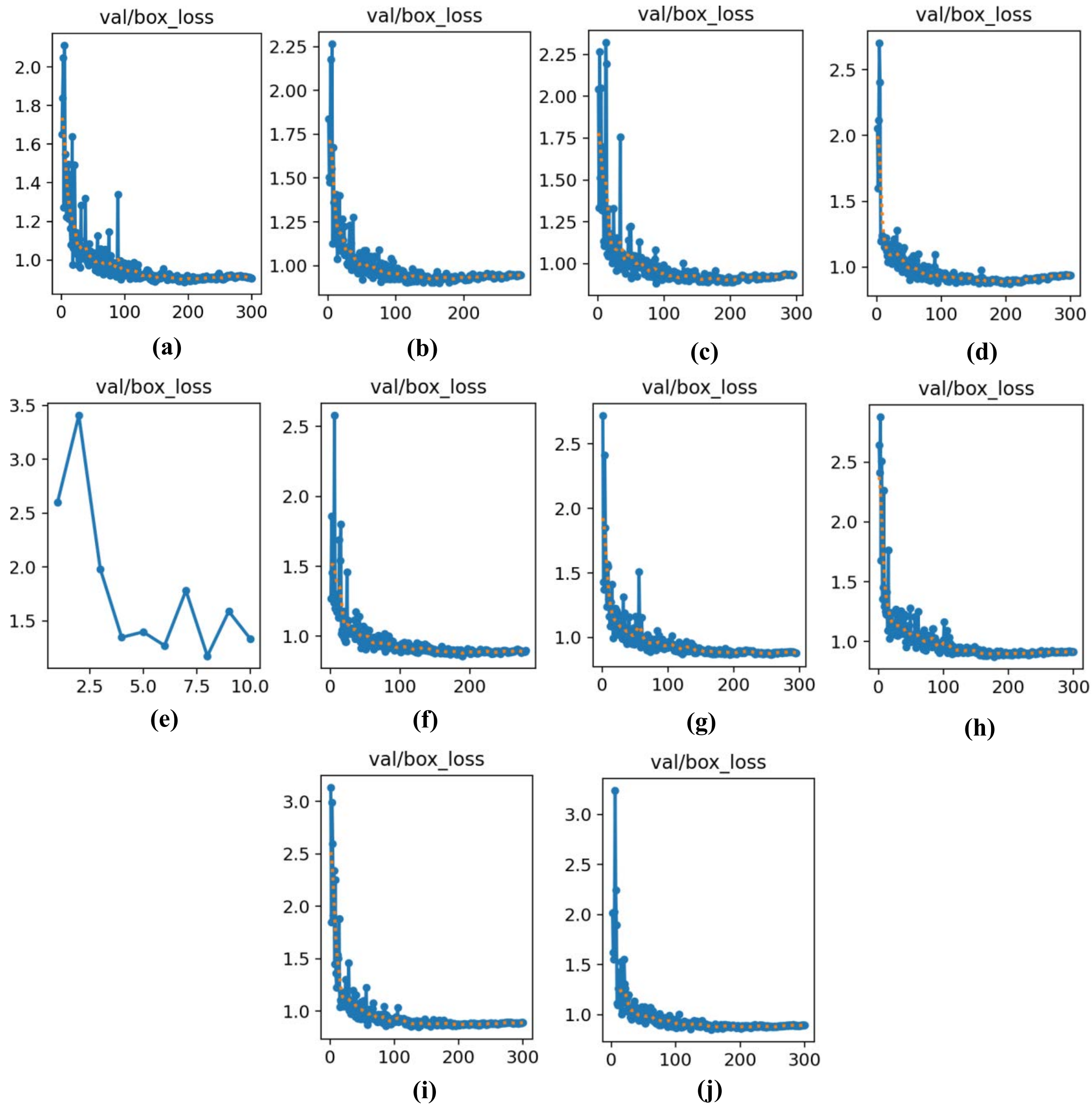


Figure 4. Loss graphs of models in validation dataset (a) YOLOv8n, (b) YOLOv8s, (c) YOLOv8m, (d) YOLOv8l, (e) YOLOv8x, (f) YOLOv11n, (g) YOLOv11s, (h) YOLOv11m, (i) YOLOv11l, (j) YOLOv11x

Precision, recall, F1-Score, mAP@0.5, mAP@0.5:0.95 and MITF performance metric values evaluated on the test data set of YOLOv8 and YOLOv11 models are presented in Table 4. When the values were examined, the YOLOv11s model provided the highest precision, F1-Score, mAP@0.5 and mAP@0.5:0.95 values with values of 0.7718, 0.7869, 0.8303 and 0.5733, respectively. The highest recall value belongs to the YOLOv11m model with a value of 0.8060. The model with the lowest performance in terms of precision, recall, F1-Score, mAP@0.5 and mAP@0.5:0.95 performance criteria was the YOLOv8x model with values of 0.5756, 0.6954, 0.6299, 0.6200 and 0.3632. In terms of inference time, the fastest model is the YOLOv11n model with a MTF value of 3.5 ms/image, and the slowest model is the YOLOv8x model with a MITF value of 49.3 ms/image. The YOLOv11s model, which showed the best performance in almost all performance criteria (except the recall criterion), had a speed of 3.5 ms/image.

Table 4. Performance metric values of the models on the test dataset

Model	**Precision**	**Recall**	**F1-Score**	**mAP@0.5**	**mAP@0.5:0.95**	**MITF (ms/image)**
YOLOv8n	0.7510	0.8037	0.7765	0.8076	0.5558	4.1
YOLOv8s	0.7308	0.7807	0.7550	0.7986	0.5514	7.6
YOLOv8m	0.7560	0.7979	0.7764	0.8193	0.5575	16.6
YOLOv8l	0.7576	0.7763	0.7668	0.8024	0.5463	25.7
YOLOv8x	0.5756	0.6954	0.6299	0.6200	0.3632	49.3
YOLOv11n	0.7477	0.7963	0.7712	0.8116	0.5554	**3.5**
YOLOv11s	**0.7718**	0.8025	**0.7869**	**0.8303**	**0.5733**	6.8
YOLOv11m	0.7386	**0.8060**	0.7708	0.8073	0.5505	14.3
YOLOv11l	0.7407	0.7631	0.7517	0.7949	0.5487	19.1
YOLOv11x	0.7340	0.7862	0.7592	0.8047	0.5478	39.0

Overall, the complexity matrix table calculated on the test dataset for the best performing YOLOv11s model is presented in Figure 5.

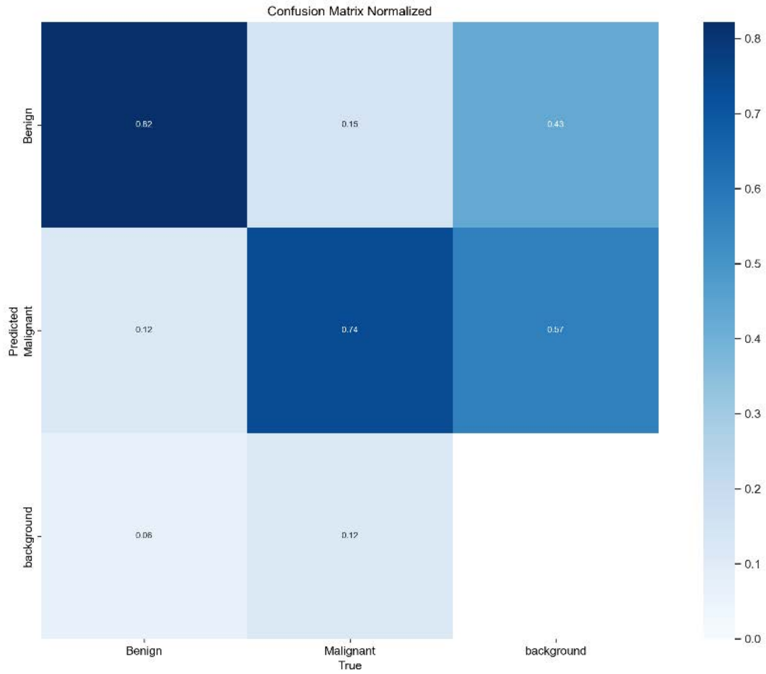


Figure 5. Table of complexity matrix for YOLOv11s model

Examples of detection results of the YOLOv11s model on the test data set are given in Figure 5.

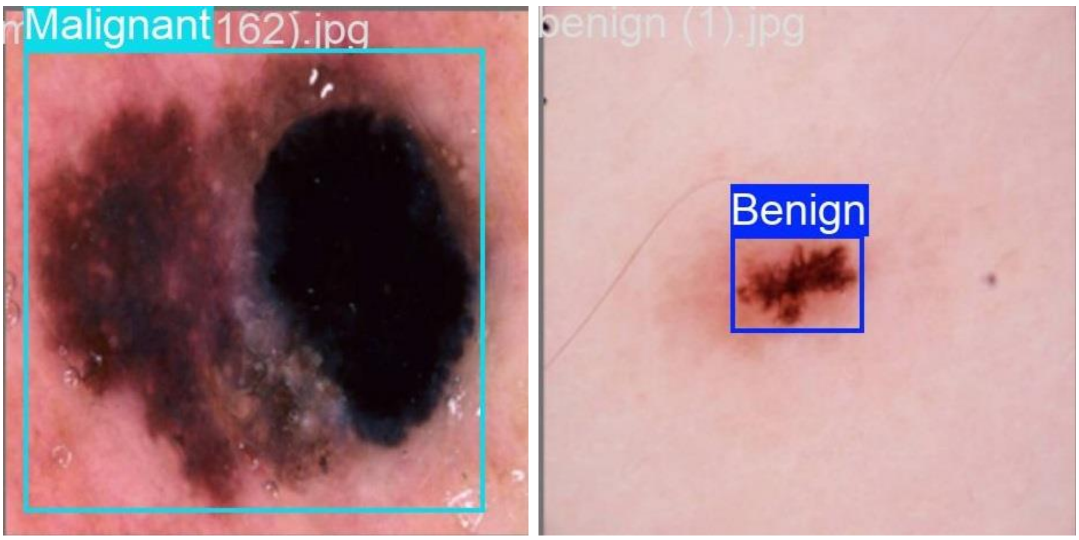


Figure 6. Sample images of detection results of YOLO v11s model

6. Conclusion

This study aimed to evaluate the performance of the deep learning-based state-of-the-art YOLOv8 and YOLOv11 algorithms in skin cancer detection using image data. The study demonstrated the success of YOLOv11 in diagnosing skin cancer. YOLOv11 offers significant advantages over previous versions in terms of speed, accuracy, and computational efficiency. In particular, the C3k2 and C2PSA modules enabled the model to identify small and complex objects more effectively.

In line with the results obtained in the study, it can be recommended to expand the use of YOLOv11 in automatic diagnosis systems in the field of health. Especially in medical image analysis, developing the model and testing it on different data sets will provide more reliable and precise results.

As a result, YOLOv11 stands out as a promising model for skin cancer diagnosis and other medical imaging applications. As a result, YOLOv11 stands out as a promising model for skin cancer diagnosis and other medical imaging applications.

In the future, development of more optimized versions of YOLOv11 to run on mobile devices and low-power hardware may facilitate the integration of the model into clinical applications. In addition, combining YOLOv11 with different medical diagnostic systems and transforming it into a versatile AI-supported analysis platform could bring innovations to the healthcare sector.

References

Aishwarya, N., Prabhakaran, K. M., Debebe, F. T., Reddy, M. S. S. A., & Pranavee, P. (2023). Skin cancer diagnosis with YOLO deep neural network. Procedia Computer Science, 220, 651-658.

Albahar, M. A. (2019). Skin lesion classification using convolutional neural network with novel regularizer. IEEE Access, 7, 38306-38313.

Albahli, S., Nida, N., Irtaza, A., Yousaf, M. H., & Mahmood, M. T. (2020). Melanoma lesion detection and segmentation using YOLOv4-DarkNet and active contour. IEEE access, 8, 198403-198414.

AlSadhan, N. A., Alamri, S. A., Ben Ismail, M. M., & Bchir, O. (2024). Skin Cancer Recognition Using Unified Deep Convolutional Neural Networks. *Cancers, 16(7)*, 1246. https://doi.org/10.3390/cancers16071246.

American Cancer Society (2023). Skin Cancer Facts & Statistics.

Ćirković, S., & Stanic, N. (2024). Application of the YOLO algorithm for Medical Purposes in the Detection of Skin Cancer. In 10th International Scientific Conference Technics, Informatics and Education-TIE 2024. Faculty of Technical Sciences Čačak, University of Kragujevac.

Datta, D., Prakash, H., & Singh, P. (2023, June). Skin Cancer Detection with Edge Devices Using YOLOv7 Deep CNN. In International Conference on Data Analytics & Management (pp. 55-63). Singapore: Springer Nature Singapore.

Demir, F. (2021). Derin öğrenme tabanlı yaklaşımla kötü huylu deri kanserinin dermatoskopik görüntülerden saptanması. Fırat Üniversitesi Mühendislik Bilimleri Dergisi, 33(2), 617-624.

Farooq, J., Muaz, M., Khan Jadoon, K., Aafaq, N., & Khan, M. K. A. (2024). An improved YOLOv8 for foreign object debris detection with optimized architecture for small objects. Multimedia Tools and Applications, 83(21), 60921-60947.

Gouda, W., Us Sama, N., Al-Waakid, G., Humayun, M., & Jhanjhi, N. Z. (2022). Detection of Skin Cancer Based on Skin Lesion Images Using Deep Learning. *Healthcare, 10(7)*, 1183. https://doi.org/10.3390/healthcare10071183.

Hasya, H. F., Nuha, H. H., & Abdurohman, M. (2021). Real Time-based Skin Cancer Detection System using Convolutional Neural Network and YOLO. *2021 4th International Conference of Computer and Informatics Engineering (IC2IE)*. https://doi.org/10.1109/IC2IE53219.2021.9649224.

Hum, Y. C., Tan, H. R., Tee, Y. K., Yap, W. S., Tan, T. S., Salim, M. I. M., & Lai, K. W. (2022). The development of skin lesion detection application in smart handheld devices using deep neural networks. *Multimedia Tools and Applications, 81*, 41579–41610. https://doi.org/10.1007/s11042-021-11013-9.

Hussain, M. (2024). Yolov5, yolov8 and yolov10: The go-to detectors for real-time vision. arXiv preprint arXiv:2407.02988.

Jegham, N., Koh, C. Y., Abdelatti, M., & Hendawi, A. Evaluating the Evolution of YOLO (You Only Look Once) Models: A Comprehensive Benchmark Study of YOLO11 and Its Predecessors. arXiv 2024. arXiv preprint arXiv:2411.00201.

Jocher, G.; Chaurasia, A.; Qiu, J. Ultralytics YOLO. 2023. Available online: https://github.com/ultralytics/ultralytics (accessed on 20 October 2024).

Jones, M., & Brown, L. (2021). Deep Learning in Dermatology: A Comprehensive Review. Artificial Intelligence in Medicine, 18(2), 67-89.

Khanam, R., & Hussain, M. Yolov11: An overview of the key architectural enhancements. arXiv 2024. arXiv preprint arXiv:2410.17725.

Li, P., Zhao, T., & Wang, Y. (2022). Medical Image Analysis Using Deep Learning Techniques. International Journal of Biomedical Imaging, 24(6), 1123-1135.

Loshchilov, I., & Hutter, F. (2017). Fixing weight decay regularization in adam. arXiv preprint arXiv:1711.05101, 5.

Malo, D. C., Khan, M. M., Rahman, M. M., & Mahbub, J. (2022). Skin Cancer Detection using Convolutional Neural Network. *2022 IEEE 12th Annual Computing and Communication Workshop and Conference (CCWC)*. https://doi.org/10.1109/CCWC54503.2022.9720751.

Nersisson, R., Iyer, T. J., Raj, A. N. J., & Rajangam, V. (2021). A Dermoscopic Skin Lesion Classification Technique Using YOLO-CNN and Traditional Feature Model. *Arabian Journal for Science and Engineering, 46*, 9797–9808. https://doi.org/10.1007/s13369-021-05571-1

Nie, Y., Sommella, P., O'Nils, M., Liguori, C., & Lundgren, J. (2019, November). Automatic detection of melanoma with yolo deep convolutional neural networks. In 2019 E-Health and Bioengineering Conference (EHB) (pp. 1-4). IEEE.

Patel, K., Sharma, R., & Kumar, N. (2023). The Role of AI in Early Diagnosis of Skin Cancer. Machine Learning in Medicine, 27(4), 567-582.

Prechelt, L. (2002). Early stopping-but when?. In Neural Networks: Tricks of the trade (pp. 55-69). Berlin, Heidelberg: Springer Berlin Heidelberg.

Ragab, M. G., Abdulkader, S. J., Muneer, A., Alqushaibi, A., Sumiea, E. H., Qureshi, R., ... & Alhussian, H. (2024). A Comprehensive Systematic Review of YOLO for Medical Object Detection (2018 to 2023). IEEE Access.

Redmon, J., Divvala, S., Girshick, R., & Farhadi, A. (2016). You Only Look Once: Unified, Real-Time Object Detection. CVPR, 779-788.

Reis, D., Kupec, J., Hong, J., & Daoudi, A. (2023). Real-time flying object detection with YOLOv8. arXiv preprint arXiv:2305.09972.

Riyadi, M. A., Ayuningtias, A., & Isnanto, R. R. (2024, September). Detection and Classification of Skin Cancer Using YOLOv8n. In 2024 11th International Conference on Electrical Engineering, Computer Science and Informatics (EECSI) (pp. 9-15). IEEE.

Rusydiyah, E. V. I. F., Novitasari, D. C. R., Mushlihul, M. F., AMIN, A. N. A., NURROHMAN, H. F., HAQ, D. Z., & PUTRI, E. R. S. (2024). Skin cancer diagnosis system on object detection using various CNN YOLOv5 in Android mobile. Journal of Theoretical and Applied Information Technology, 102(15).

Santos, C., Aguiar, M., Welfer, D., & Belloni, B. (2022). A new approach for detecting fundus lesions using image processing and deep neural network architecture based on YOLO model. Sensors, 22(17), 6441.

Sapkota, R., Meng, Z., Churuvija, M., Du, X., Ma, Z., & Karkee, M. (2024). Comprehensive performance evaluation of yolo11, yolov10, yolov9 and yolov8 on detecting and counting fruitlet in complex orchard environments. arXiv preprint arXiv:2407.12040.

Smith, J., Doe, A., & Green, R. (2022). Advances in Early Skin Cancer Detection. Journal of Oncology Research, 15(3), 123-135.

Soni, A., & Rai, A. (2024, June). YOLO for Medical Object Detection (2018–2024). In 2024 IEEE 3rd International Conference on Electrical Power and Energy Systems (ICEPES) (pp. 1-7). IEEE.

Sutaji, D., & Yildiz, O. (2023). YOLOv8's head-layer Performance Comparison for Skin Cancer Detection. In Proceeding of International Conference of Advance Transportation, Engineering, and Applied Social Science (Vol. 2, No. 1, pp. 1036-1042).

Tabrizchi, H., Parvizpour, S., & Razmara, J. (2023). An Improved VGG Model for Skin Cancer Detection. *Neural Processing Letters, 55*, 3715–3732. https://doi.org/10.1007/s11063-022-10927-1.

Tchema, R. B., Nestoros, M., & Polycarpou, A. C. (2024, June). Computer-Aided Classification of Skin Cancer based on the YOLO Algorithm. In 2024 13th International Conference on Modern Circuits and Systems Technologies (MOCAST) (pp. 1-4). IEEE.

Terven, J., Córdova-Esparza, D. M., & Romero-González, J. A. (2023). A comprehensive review of yolo architectures in computer vision: From yolov1 to yolov8 and yolo-nas. Machine Learning and Knowledge Extraction, 5(4), 1680-1716.

Tuncer, T., Barua, P. D., Tuncer, I., Dogan, S., & Acharya, U. R. (2024). A lightweight deep convolutional neural network model for skin cancer image classification. *Applied Soft Computing*. https://doi.org/10.1016/j.asoc.2024.111794.

Ultralytics (2023). YOLOv8: Real-Time Object Detection and Classification. Technical Report.

Wang, L., & Lee, C. (2021). Performance Evaluation of Deep Learning Models in Medical Image Classification. Medical AI Journal, 19(5), 98-115.

Zhang, Y., Liu, X., & Chen, W. (2023). YOLOv11: Next Generation Object Detection Model. IEEE Transactions on Image Processing, 32, 2105-2118.

Paper #37

Title: Blockchain Technology for Supply Chain Management: An Overview of Use Cases and Benefits

Author(s): Zeynep Kubilay, Merve Şişci and İsmail Hakkı Cedimoğlu

Abstract:
This paper reviews the application of blockchain technology in supply chain management, focusing on transparency, traceability, and security. It analyzes real-world use cases and highlights the operational benefits of decentralized ledgers. The study concludes that blockchain adoption can significantly improve supply chain efficiency and stakeholder trust.

Keywords: Blockchain, Supply Chain, Traceability, Transparency, Decentralized Systems

Paper #60

Title: Perceived Ambivalence and Continuance Usage of Chatbots in Online Retailing

Author(s): Hajer Kefi (Université Paris-Panthéon-Assas)

Abstract:
This paper examines how perceived ambivalence—users simultaneously accepting and resisting chatbot technology—affects continued usage in online retail. Based on a survey of 218 French consumers, findings show that perceived benefits foster acceptance while privacy concerns fuel resistance. Ambivalence is shown to significantly shape long-term engagement, offering insights for improving chatbot design and user retention.

Keywords: Chatbots, Ambivalence, Online Retail, User Behavior, Technology Adoption

Paper #33

Title: The Dead Internet Theory and Brain Rot: An Evaluation from the Perspective of Social Media

Author(s): Sinem Mizanalı (Istanbul Gedik University) and Nihal Sütütemiz (Sakarya University)

Abstract:
This paper explores the intersection of the Dead Internet Theory and the phenomenon of "Brain Rot" in the age of AI-generated content. It analyzes how automation on social media platforms diminishes genuine human interaction and impacts cognitive functions. Drawing on recent studies and digital behavior trends, the authors advocate for digital literacy programs and algorithmic transparency to mitigate these effects.

Keywords: Dead Internet Theory, Brain Rot, Social Media, Artificial Intelligence, Digital Literacy

The Dead Internet Theory and Brain Rot: An Evaluation from the Perspective of Social Media

Sinem Mizanalı[1,2], Nihal Sütütemiz[3]

[1]Istanbul Gedik University, Department of Computer Engineering, Research Assistant, Istanbul, Türkiye, sinem.mizanali@gedik.edu.tr

[2]Sakarya University, Department of Management Information Systems, PhD Student, Sakarya, Türkiye, sinem.mizanali@ogr.sakarya.edu.tr

[3]Sakarya University, Department of Management Information Systems, Sakarya, Türkiye, nihals@sakarya.edu.tr

ABSTRACT

This study provides a conceptual analysis of the growing dominance of artificial intelligence (AI)-generated content on social media platforms and examines this process through the lens of the Dead Internet Theory and the emerging concept of Brain Rot. The Dead Internet Theory suggests that the internet is increasingly populated by AI-generated content, while authentic human contributions are gradually diminishing. Simultaneously, the term *Brain Rot* describes a cognitive decline observed in users as a result of prolonged exposure to low-quality, repetitive and superficial digital content. Drawing upon recent findings and public discourse, the study presents a conceptual model that illustrates how algorithm-driven content dissemination fosters a feedback loop between user demand and AI-generated media. This process not only reinforces automated content production but also contributes to the cognitive effects associated with Brain Rot. The study concludes with recommendations for future research and policy development, including experimental investigations and the promotion of digital literacy, particularly among younger users.

Keywords: Dead Internet Theory, Brain Rot, Social Media

INTRODUCTION

Since the 1990s, internet technology has become an indispensable part of individual and societal life, leading to significant transformations across various domains. With the acceleration of digitalization, the internet has evolved from being merely a medium for information sharing into a space for content production and consumption. However, recent advancements in artificial intelligence technologies have sparked new debates regarding whether online content is genuinely user-generated or artificially created. In this context, the Dead Internet Theory argues that the internet is increasingly filled with content generated by artificial intelligence, while content created by real individuals is gradually diminishing. While this theory was previously regarded as merely a conspiracy theory, appearing in various news articles and personal blogs, the growing influence of artificial intelligence has made its implications more visible in everyday life (Walter 2024). With this transformation it can be argued that the internet is losing its function as a space for human-generated information and interaction, instead becoming a structure dominated by automated content. Although this theory was initially considered a conspiracy theory, the rapid rise of AI-assisted content generation has increasingly made it a subject of academic research (Broad 2024; Muzumdar et al. 2025; Türkelli and Çelik 2024; Walter 2024).

Although the Dead Internet Theory remains an unproven claim the increasing invisibility of human-generated content on the internet, the entrapment of users within algorithmic filter bubbles (Pariser 2011) and the growing influence of social bots within the content ecosystem provide a foundational basis for the phenomenon of artificialized social media that the theory points to.

The Dead Internet Theory suggests that the internet has shifted from being a human-centered medium of communication to one increasingly driven by automation. Zuboff (2018) argues that algorithmic systems manipulate user behavior and promote the automated production of content. In this context, the Dead Internet Theory provides a framework claiming that human interactions are declining as social media platforms become saturated with content generated by bots and artificial intelligence. Furthermore, filter bubbles are believed to confine users within personalized content loops through social media algorithms, thereby diminishing genuine interactions (Pariser 2011). This phenomenon further supports the premises of the Dead Internet Theory.

Artificial Content Ecosystems and Social Media

With the advancement of artificial intelligence technologies, content production on the internet has become largely automated. In particular, social media accounts that generate revenue by utilizing low-quality (Broad 2024), AI-generated content—commonly referred to as Content Farms —provide concrete evidence that reinforces the Dead Internet Theory. One of the central claims of this theory is that a significant portion of the images, videos, audio and text encountered on social media is not created by humans but by artificial intelligence (Broad 2024). According to the 2024 Imperva Threat Research report, approximately 50% of internet traffic originates from non-human sources (Imperva 2024). Furthermore, as social media content becomes increasingly artificial, individuals are transformed into digital consumers, pushing real human interactions into the background (Muzumdar et al. 2025).

The Concept of Brain Rot

In recent years, the presence of AI-generated content on social media and the increasing prevalence of social media addiction have had negative effects on users' mental and intellectual capacities. In this context, Oxford University, through a survey involving over 37,000 participants, selected the term "Brain Rot" as the Word of the Year for 2024. This concept refers to the deterioration of individuals' cognitive functions as a result of excessive consumption of digital content (Oxford University 2024). The term "Brain Rot" is particularly associated with the decline in users' attention spans and the experience of cognitive fatigue due to the low-quality, repetitive and superficial nature of content produced on social media.

Conceptual Model

This study examines the intersection between the Dead Internet Theory, which addresses the increasing dominance of AI-generated content on social media platforms and the concept of "Brain Rot," which refers to the cognitive effects associated with prolonged digital media exposure. To present this relationship in a clear and structured way, a conceptual model is provided in Figure 1.

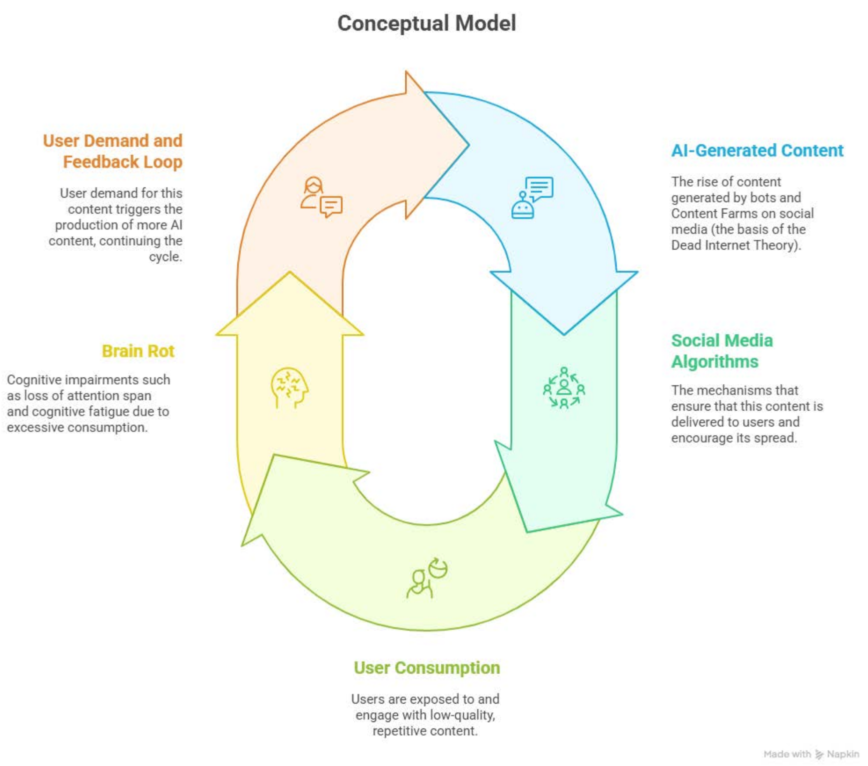


Figure 1. Conceptual Model

The model illustrates how content generated by artificial intelligence—often produced by bots and content farms—is disseminated to users through social media algorithms, forming a self-perpetuating cycle. In the initial stage, low-quality and repetitive AI-generated content is circulated across platforms, aided by algorithms that prioritize user engagement metrics. These algorithms increase the visibility of such content based on users' previous interactions. Users are then passively exposed to and engage with this content.

Continuous exposure to this type of superficial and repetitive content leads to cognitive impairments such as reduced attention span, mental fatigue and a decline in critical thinking—symptoms commonly associated with Brain Rot. In the final stage of the cycle, the user's engagement is interpreted as demand by the system, prompting the production and distribution of even more AI-generated content. This completes a feedback loop, reinforcing the presence of artificial content in the digital ecosystem.

The model not only describes the flow of content but also clarifies the role of users within this system. Although users may not actively contribute to content creation, they become passive producers by influencing algorithmic decision-making through their consumption behavior. This cyclical structure offers a conceptual framework that supports the core claims of both the Dead Internet Theory and the Brain Rot phenomenon.

Conclusion and Recommendations

This study conceptually examines the common ground between the Dead Internet Theory, which is associated with the increasing dominance of artificial content on social media and the concept of "Brain Rot," which is similarly linked to social media use. To enhance understanding of the issue, the study proposes a conceptual model.

Future research could empirically test the Dead Internet Theory using data mining techniques to analyze the proportion of AI-generated content on social media platforms. Furthermore, experimental studies could be designed to examine the effects of "Brain Rot" by evaluating the relationship between social media usage duration and critical thinking or attention performance. In this context, regulating social media algorithms, clearly labeling AI-generated content, implementing educational programs and seminars to enhance digital literacy are recommended. Participation in such programs should be especially encouraged among younger users.

REFERENCES

Broad, T. 2024. "Is Computational Creativity Flourishing on the Dead Internet?," in: *ICCC'24: 15th International Conference on Computational Creativity*. Jönköping, Sweden.

Imperva. 2024. "2024 Bad Bot Report."

Muzumdar, P., Cheemalapati, S., RamiReddy, S. R., Singh, K., Kurian, G., and Muley, A. 2025. "The Dead Internet Theory: A Survey on Artificial Interactions and the Future of Social Media," *Asian Journal of Research in Computer Science* (18:1), pp. 67-73.

Oxford University. 2024. "'Brain Rot' Named Oxford Word of the Year 2024." 14.02.2025, from https://corp.oup.com/news/brain-rot-named-oxford-word-of-the-year-2024/

Pariser, E. 2011. *The Filter Bubble: What the Internet Is Hiding from You*. New York: Penguin Press.

Türkelli, N., and Çelik, B. 2024. "Yapay Zeka Ve Botların Gölgesinde Kamusal Alanın Geleceği: Ölü İnternet Teorisi," in: *Toplumsal Araştırmalar Merkezi (TAM) 3. Uluslararası Sosyal Bilimler Kongresi*. Antalya, Türkiye: pp. 40-43.

Walter, Y. 2024. "Artificial Influencers and the Dead Internet Theory," *AI & SOCIETY*).

Zuboff, S. 2018. *The Age of Surveillance Capitalism: The Fight for a Human Future at the New Frontier of Power*. New York: Public Affairs.

Paper #27

Title: A Social Media Perspective on the First Three Days of the February 6 Earthquakes

Author: Oğuzhan Arı

Abstract:
This study investigates how social media, particularly X (formerly Twitter), captured public reactions and support efforts following the February 6, 2023, earthquakes in Türkiye. By analyzing over 4 million entries from the first three days after the disaster, the research highlights peaks in interaction, the spread of emergency information, and the role of citizens, media, and NGOs. It also discusses limitations caused by government-imposed platform restrictions.

Keywords: Social Media, Natural Disasters, Earthquake, Crisis Communication, Türkiye

Paper #26

Title: Model Optimization and Energy Efficiency in Deep Learning-Based Image Classification on Edge Devices

Author(s): Asım Bilal Yılmaz and Fatih Çallı (Sakarya University)

Abstract:
This study examines the performance and energy efficiency of deep learning image classification on edge devices. By integrating model compression techniques, such as pruning and quantization, with lightweight architectures like MobileNet, EfficientNet, and ShuffleNet, the authors conduct systematic experiments across various devices, including AMD NPU, Google Coral TPU, and NVIDIA Jetson Nano. The findings offer a framework for deploying efficient and sustainable AI on edge hardware.

Keywords: Deep Learning, Image Classification, Edge Devices, Model Optimization, Energy Efficiency

Paper #29

Title: A Mobile Application for Evaluating Physical Therapy Exercises Using Image Processing and Deep Learning

Author(s): Ayşe Gül Kiliç and Mehmet Ulaş Koyuncuoğlu

Abstract:
This paper presents a mobile application that uses computer vision and deep learning to guide patients through personalized physical therapy exercises. By analyzing body movements and offering real-time feedback, the system ensures correct execution and supports home-based rehabilitation. Developed using tools such as Flutter, Firebase, and CNN-based models, the application demonstrates high accuracy and usability. It aligns with global health goals by improving patient outcomes and reducing medical costs.

Keywords: Physical Therapy, Mobile Application, Image Processing, Deep Learning

Paper #51

Title: Global Issues in Artificial Intelligence: A Literature Review and Research Agenda

Author: Tim Jacks (Southern Illinois University Edwardsville)

Abstract:
This work-in-progress paper explores pressing global issues in artificial intelligence (AI), with a focus on generative AI and large language models. Based on an extensive literature review, the study identifies research gaps and proposes a comprehensive agenda for future work in global IT management. Key themes include the societal impact of AI, regulatory disparities, ethical considerations, and global digital inequality. The paper aims to inform both academics and practitioners about the emerging challenges and opportunities in AI.

Keywords: Artificial Intelligence, Global IT Management, Generative AI, Literature Review, Research Agenda

Paper #32

Title: The Role of AI Bias in Amplifying Misinformation and Disinformation

Author: Abdullah Oguz and Hassan A. Ahmed

Abstract:
This extended abstract examines how algorithmic bias in AI systems contributes to the dissemination of misinformation and disinformation, particularly through the use of generative models. The paper identifies research gaps in current mitigation strategies and proposes a bias-aware artificial intelligence (AI) framework. Future work includes user behavior studies and ethical guidelines to promote fairness in AI-generated content across digital platforms.

Keywords: AI Bias, Misinformation, Disinformation, Generative AI, Algorithmic Fairness

Paper #16

Title: Compensating Data Loss from Head Rotations in Single-Image Texture Completion by Diffusion Probabilistic Model

Author(s): Onuralp Gayret and Aydın Erden (Sakarya University)

Abstract:
This paper addresses data loss in 3D facial texture reconstruction caused by vertical head rotations in single-image inputs. Using Shannon entropy to measure occlusion-related loss, the authors propose a solution based on Denoising Diffusion Probabilistic Models (DDPMs). The approach improves texture completion under severe occlusions, with potential applications in biometrics and VR.

Keywords: Texture Completion, 3D Face Modeling, Head Rotation, Diffusion Models, Occlusion

Paper #63

Title: Green Software Development: An Empirical Study on Awareness, Practices, and Challenges

Author(s): Keziban Seckin Codal and Eda Sönmez

Abstract:
This paper investigates awareness and implementation of green software development practices among software engineers. Based on a survey of 150 professionals, the study explores the integration of sustainability into software design, development, and deployment. Findings indicate a growing interest but limited application due to knowledge gaps and organizational constraints.

Keywords: Green Software, Sustainable Development, Software Engineering, Energy Efficiency, Environmental Impact

SHIFTS IN SMART CITY PERFORMANCE: A COMPARATIVE CLUSTERING STUDY OF OECD CITIES

ABSTRACT

Smart city research has evolved into one of the most active fields to optimize city functions and improve the quality of life. This study examines the performance of OECD cities across all subdomains within the structural and technological pillars of smart cities—namely health and safety, mobility, activities, opportunities, and governance. It also provides a comprehensive comparison analysis spanning the years 2023 and 2024. Finally, the findings reveal four distinct clusters: Cities in the first cluster demonstrate superior performance in structural aspects, excelling in managing smart city infrastructure. Cities in the second cluster are distinguished by their advanced technological focus. The third cluster, while exhibiting lower performance than Cluster 1 and higher performance than Cluster 4, demonstrates a commitment to ongoing progress in both pillars. Cities belonging to the fourth cluster, lagging in both structural and technological advancements, require substantial urban development efforts to address deficiencies and elevate their smart city capabilities. In the separate assessment of the technology and structure pillars, cities generally show a higher level of performance in structural domains compared to their technological counterparts. Among subdomains, traffic management emerges as a critical area requiring improvement across all clusters. Conversely, the domain of activities excels with the highest scores in both the structural and technological pillars. This analysis enhances our understanding of smart city development and identifies strengths and weaknesses within each cluster. It provides actionable insights for policymakers and urban planners to refine smart city strategies and improve overall performance.

Keywords : smart cities, OECD, clustering

1. INTRODUCTION

Urbanization is one of the most significant concepts in modern society, and its rate is still rising. The global population is projected to keep increasing over the next fifty to sixty years, potentially hitting about 10.3 billion by the mid-2080s (United Nations Department of Economic and Social Affairs, 2024). With the high pace of urbanization, problems like overcrowding, inadequate urban design or planning, ineffective public transportation, poor governance, climate change-related problems, inadequate sewerage and water infrastructure, waste and health-related problems, unemployment, unusually fragile infrastructure, increase in crime, and environmental issues have started to emerge (Khan et al., 2022). The concept of "smart city" has evolved as one of the potential solutions to these problems.

The idea of "smart cities" has evolved into three stages over the past few decades: strengthening building infrastructure, ensuring health and safety, and utilizing information and communication technology (ICT) solutions (Ammara et al., 2022). The infrastructures are essential to make cities more efficient and undeniably affect cities' productivity, economy, and security. On the other hand, the advancement of digital technologies has led to their increased application across various dimensions of daily life and societal well-being (Fakhimi et al., 2021)

Although there is no universally accepted definition of a smart city (Hollands, 2008), examining its components is essential for gaining insights into a holistic vision. Sharma and colleagues (2023) identified six key components that significantly improve the overall functionality of cities and the quality of life for their residents. Smart economy is vital, fostering a thriving business environment that boosts prosperity and productivity through entrepreneurship and innovation. This attracts a skilled workforce and supports a startup culture. Smart living focuses on improving residents' quality of life by enhancing education, health services, and recreational facilities, which strengthens community ties and encourages social interaction. Smart governance emphasizes citizen participation in decision-making, ensuring that policies reflect the needs of the community while promoting transparency through open data and digital services. The smart people aspect highlights the importance of engaged and knowledgeable citizens who actively contribute to local governance and embrace lifelong learning. Additionally, the smart environment component prioritizes sustainability by advocating for resource efficiency and the use of renewable energy to reduce environmental impacts. Lastly, smart mobility leverages advanced technologies to improve urban transportation, tackle traffic issues, and promote eco-friendly transport options. Collectively, these elements illustrate the intricate ways in which social, economic, and environmental factors are interwoven to create a more sustainable and resilient urban future.

The majority of research on smart cities focuses on fundamental topics such as terminology and definitions (Albino et al., 2015; Anthopoulos, 2015; Dameri & Dameri, 2013; Kondepudi & Kondepudi, 2019), applications (Eckhoff & Wagner, 2018; Lau et al., 2019), benefits and problems (Arroub et al., 2016; Huang et al., 2021). Studies comparing smart cities mainly employed the case study methodology (Caird, 2017; Mattoni et al., 2020; Petritoli et al., 2019) and compared just a few cities (Cowley et al., 2018; Sancino & Hudson, 2020; Simonofski et al., 2021).

While existing literature predominantly emphasizes the components and theoretical aspects of smart cities, a thorough evaluation of their performance is crucial. Such evaluations offer critical insights into the actual effectiveness of smart city projects and serve as a foundation for evidence-based policy interventions. By enabling decision-makers at both national and international levels to set realistic goals, monitor progress, and refine strategies, performance assessments significantly enhance the efficiency and impact of smart city initiatives (OECD, 2020a).

In this context, clustering methods have emerged as powerful tools for grouping cities based on various performance metrics and indexes such as (IESE, 2019), IMD (2023), thereby facilitating the identification of cities with similar performance profiles. For instance, Cantuarias-Villessuzanne et al., (2021) employed hierarchical ascending classification to evaluate the smart city performance of European cities, with a specific focus on sustainability. Their study analyzed seven key dimensions across 40 cities using data from three indexes: The IESE Cities in Motion Index, The IMD Smart City Index, and The Easypark Smart Cities Index, all from 2019.

In a more recent study, Kenger et al., (2023) applied three different clustering techniques to evaluate smart city performance, utilizing updated data from the IMD Smart City Index for 2023. This approach allowed for a comparative analysis of clustering outcomes and offered fresh insights into the evolving landscape of smart city performance.

Our study makes a significant contribution to the existing literature by utilizing a more recent dataset and conducting a comparative analysis over a two-year period, 2023 and 2024. This approach allows us to observe whether notable changes in city performance have occurred over time. Moreover, instead of merely evaluating the overall performance of cities within clusters, we adopt a holistic approach by conducting a detailed examination of performance across all subdomains within the structural and technological pillars of smart city development—namely health and safety, mobility, activities, opportunities, and governance. This comprehensive analysis not only enhances our understanding of smart city dynamics and their evolution but also provides a detailed view of the strengths and weaknesses within each cluster.

2. METHODOLOGY

2023 and 2024 data from The IMD Smart City Index (SCI) was chosen for clustering smart cities because it is up-to-date and covers a wide range of urban characteristics. Its detailed attributes and recent updates make it ideal for analyzing current trends and performance in smart city performance.

The Smart City Index (SCI), developed by IMD, measures how citizens perceive the structures and technological applications that are available in their city. Using the opinions of 120 residents in each city, the 2023 edition ranks 141 cities, and the 2024 edition ranks 142 cities across the globe. Residents' opinions are collected for two pillars: the structures pillar, which refers to the city's current infrastructure, and the technology pillar, which describes the technological services and facilities accessible to locals. Each pillar is assessed in five critical domains: health and safety, mobility, activities, opportunities, and governance, and 39 subdomains are assessed in total under these domains. All questions in the IMD Smart City Index are given in Appendix A.

Our research questions are:

RQ1: Can OECD cities be divided into categories based on the perceived level of smart city development?

RQ2: What are the prominent strengths and weaknesses of the clusters?

RQ3: How have the clusters evolved from 2023 to 2024? Are there noticeable shifts in cluster membership?

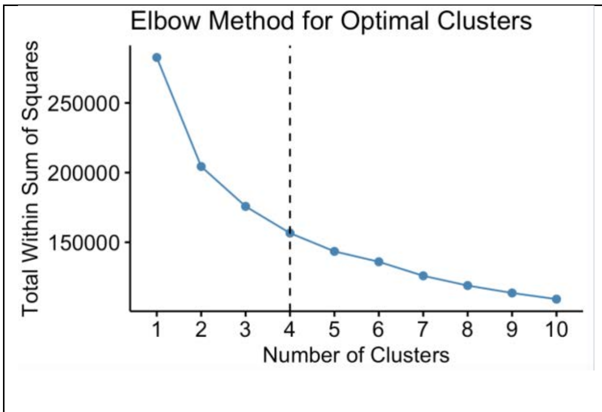
We narrowed the scope of research to OECD cities. The visions for the OECD for the next decade include maintaining its work on science, innovation, and digitalization as well as assisting open societies in the digital and data-driven age (OECD, 2021). The OECD also focuses on the smart city issue and has published many papers to inform, encourage, and develop new skills in response to the difficulties associated with digitalization and smart city efforts (OECD, 2019, 2020b, 2020c, 2023).

In this respect, we grouped 85 cities (Amsterdam, Ankara, Athens, Auckland, Barcelona, Belfast, Berlin, Bilbao, Birmingham, Bogota, Bologna, Bordeaux, Boston, Bratislava, Brisbane, Brussels, Budapest, Busan, Canberra, Cardiff, Chicago, Copenhagen, Denver, Dublin, Dusseldorf, Geneva, Glasgow, Gothenburg, Hamburg, Hanover, Helsinki, Istanbul, Kiel, Krakow, Lausanne, Leeds, Lille, Lisbon, Ljubljana, London, Los Angeles, Luxembourg, Lyon, Madrid, Manchester, Marseille, Medellin, Melbourne, Mexico City, Milan, Montreal, Munich, New York, Newcastle, Osaka, Oslo, Ottawa, Paris, Philadelphia, Phoenix, Prague, Reykjavik, Riga, Rome, Rotterdam, San Francisco, San Jose, Santiago, Seattle, Seoul, Stockholm, Sydney, Tallinn, Tel Aviv, The Hague, Tokyo, Toronto, Vancouver, Vienna, Vilnius, Warsaw, Washington D.C., Wellington, Zaragoza, Zurich) which are members of OECD countries that are in the index with K-means clustering algorithm for the first research question, because it is most well-known and used clustering method (Sinaga & Yang, 2020). K-means is utilized because it automatically computes the centroids of clusters, effectively creating homogeneous groups where data points exhibit similar characteristics. This method allows for efficient dataset partitioning, enabling the identification of distinct patterns.

K-means is a fundamental unsupervised learning algorithm designed to address the clustering problem. It operates by partitioning a dataset into a predefined number of clusters, denoted as k. The algorithm starts by initializing k centroids, each representing the center of a cluster. The placement of these initial centroids is crucial, as their locations can significantly influence the clustering outcome. Ideally, centroids should be positioned as far apart from each other as possible to enhance the clustering process. The algorithm proceeds by assigning each data point in the dataset to the nearest centroid based on a chosen distance metric. Once all points are assigned, the first iteration completes, forming preliminary clusters. The next step involves recalculating the centroids as the mean positions of the data points within each cluster until each data point is assigned (Kenger et al., 2023; Kodinariya & Makwana, 2013).

3. RESULT AND DISCUSSION

It's crucial to figure out the optimum number of clusters (k) in a K-means clustering technique. The elbow approach is a valuable technique for determining the ideal value of k. Figure 1a and Figure 1b provide the scree plot from the elbow approach for 2023 and 2024.



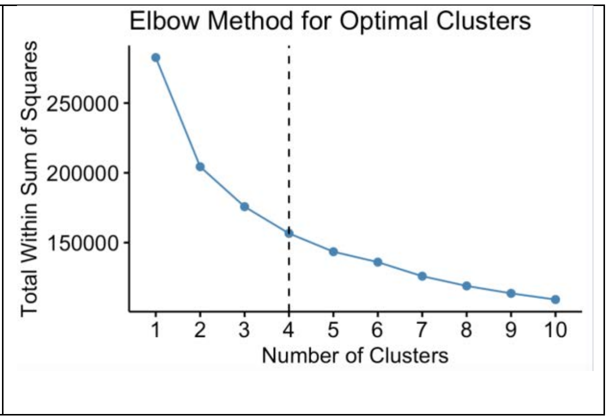


Figure 1a. Scree Plot for 2023 Data **Figure 1b. Scree Plot for 2024 Data**

The plots show a distinct elbow at k=4, suggesting that four clusters are optimal for 2023 and 2024. Beyond this point, the rate of decrease in the Within sum of squares (WCSS) becomes less pronounced. The sizes of clusters are 15, 23, 31, and 16, respectively, for 2023 and 14, 24, 32, and 15, respectively, for 2024. The result of the clustering analysis is given in Table 1.

Table 1. Grouping of OECD cities based on the perceived smart city performance levels in 2023 and 2024

Year	Cluster Number	Cluster Members
2023	1	Bilbao, Brisbane, Canberra, Copenhagen, Geneva, Helsinki, Lausanne, Luxembourg, Munich, Oslo, Prague, Tallinn, Vienna, Zaragoza, Zurich
	2	Amsterdam, Ankara, Barcelona, Bologna, Bordeaux, Brussels, Busan, Chicago, Krakow, Lille, London, Los Angeles, Lyon, Madrid, Medellin, Milan, New York, Paris, Seoul, Sydney, Vilnius, Warsaw, Washington D.C.
	3	Auckland, Belfast, Berlin, Birmingham, Boston, Bratislava, Cardiff, Denver, Dublin, Dusseldorf, Glasgow, Gothenburg, Hamburg, Hanover, Kiel, Leeds, Ljubljana, Manchester, Melbourne, Montreal, Newcastle, Ottawa, Phoenix, Reykjavik, Rotterdam, San Francisco, Stockholm, The Hague, Toronto, Vancouver, Wellington
	4	Athens, Bogota, Budapest, Istanbul, Lisbon, Marseille, Mexico City, Osaka, Philadelphia, Riga, Rome, San Jose, Santiago, Seattle, Tel Aviv, Tokyo
2024	1	Bilbao, Canberra, Copenhagen, Geneva, Hanover, Helsinki, Lausanne, Luxembourg, Munich, Oslo, Tallinn, Vienna, Zaragoza, Zurich

	2	Amsterdam, Ankara, Barcelona, Bordeaux, Bratislava, Brussels, Budapest, Busan, Chicago, Krakow, Lille, Ljubljana, London, Los Angeles, Lyon, Madrid, Medellin, New York, Paris, Prague, Riga, Seoul, Vilnius, Warsaw
	3	Auckland, Belfast, Berlin, Birmingham, Boston, Brisbane, Cardiff, Denver, Dublin, Dusseldorf, Glasgow, Gothenburg, Hamburg, Kiel, Leeds, Manchester, Melbourne, Montreal, Newcastle, Ottawa, Phoenix, Reykjavik, Rotterdam, San Francisco, Seattle, Stockholm, Sydney, The Hague, Toronto, Vancouver, Washington D.C., Wellington
	4	Athens, Bogota, Bologna, Istanbul, Lisbon, Marseille, Mexico City, Milan, Osaka, Philadelphia, Rome, San Jose, Santiago, Tel Aviv, Tokyo

The distribution of cities in Table 1, coupled with the stability in cluster sizes, indicates only minor changes from 2023 to 2024. This suggests that the overall distribution of cities across clusters has remained relatively consistent over the year. To further explore this stability and gain a deeper understanding of the characteristics defining each cluster, we can analyze the cluster means of key smart city indicators across five domains in the context of the structure and technology pillars. Examining these cluster means provides an average measure of performance across all cities in that cluster, offering insights into the strengths and weaknesses of each cluster about these indicators.

Table 2 shows the cluster means of the health and safety questions under the structure level**.** We abbreviate parameters as S_XY, where S refers to the "structure," X is for the domain, which includes H-health and safety, M-mobility, A-activities, O-opportunities, and G-governance, and Y stands for the number of questions in Tables.

Table 2. Cluster Means of the Health and Safety Questions under the Structure Pillar for 2023 and 2024

Year	**Clusters**	**S_H1**	**S_H2**	**S_H3**	**S_H4**	**S_H5**	**S_H6**
2023	**1**	74.64667	77.14000	65.78667	73.12667	55.12000	26.62667
	2	62.05217	65.50000	48.09565	30.17391	61.01304	33.10870
	3	62.81613	68.13226	47.99032	43.79677	59.07742	24.73548
	4	49.42500	48.94375	35.91875	27.77500	49.65625	26.78750
	1	73.90000	76.77143	64.01429	56.37143	70.98571	27.24286

2024	2	60.26250	63.46250	49.29167	31.88750	56.50000	27.86250
	3	60.73125	66.80000	42.92188	44.12500	57.95000	22.55938
	4	53.30000	52.55333	33.99333	26.44000	52.03333	32.32667

Table 2 shows that the first cluster excels consistently high scores across four questions for 2023. These questions are related to basic sanitation needs (S_H1), recycling services (S_H2), public safety (S_H3), and air pollution (S_H4). Notably, Cluster 1 exhibits a pronounced strength in addressing air pollution compared to other clusters, as evidenced by the fourth question mean in Table 2. In 2023, Cluster 2 has higher average scores for the fifth (satisfaction with medical services) and sixth (finding housing with rent equal to 30% or less of a monthly salary) questions related to other clusters. This indicates that cities in Cluster 2 perform better regarding medical services and affordable housing. Cluster 4 generally has the lowest average scores across all questions. This suggests that cities in Cluster 4 face challenges in health and safety smart city dimensions. For 2024, Cluster 1 maintains its leading position with the highest average scores in most components. However, there is a noticeable decline in the average score for air pollution, coupled with a significant rise in the score for satisfaction with medical services. This shift suggests a potential strategic redirection or reallocation of resources. It appears that cities in Cluster 1 may have prioritized improvements in medical services, possibly at the expense of air quality management. Cluster 4 continues to have the lowest average scores across most components, except for the sixth component, where its performance remains relatively low but shows some variation.

Table 3. Cluster Means of the Mobility and Activities Questions under the Structure Pillar for 2023 and 2024

Year	Clusters	S_M1	S_M2	S_A1	S_A2
2023	1	37.70000	69.41333	74.66667	81.48000
	2	27.15217	59.70000	65.63913	76.10870
	3	27.07097	52.85161	65.72581	76.15484

	4	19.56250	40.78750	50.17500	66.64375
2024	**1**	39.48571	69.44286	75.53571	81.52143
	2	26.40000	58.35833	62.34167	75.02917
	3	25.36875	51.95938	64.43125	76.29688
	4	20.20000	41.95333	52.10000	69.22000

The first question in the mobility domain, which focuses on traffic congestion (S_M1), shows notably low averages across all clusters, as illustrated in Table 3. This indicates that traffic congestion has been a significant issue for all-cluster cities over the years. Cluster 4 stands out with the lowest scores for traffic congestion. This suggests that cities in Cluster 4 struggle the most with managing traffic flow and congestion.

While traffic congestion is a concern for other clusters, it is less severe than Cluster 4 in all-time intervals. Clusters 1, 2, and 3 have relatively higher average scores, indicating somewhat better traffic management, though still facing challenges.

The second question in the activities domain (cultural activities are satisfactory), S_A2, has the highest average score, particularly in Cluster 1. This indicates that cities in Cluster 1 provide a high level of cultural activities, leading to greater satisfaction among residents. The patterns are consistent when comparing the average scores for 2023 and 2024. The performance in mobility and activities remains similar across both years.

Table 4. ***Cluster Means of the Opportunities Questions under the Structure Pillar for 2023 and 2024***

Year	**Clusters**	**S_O1**	**S_O2**	**S_O3**	**S_O4**	**S_O5**
2023	**1**	71.65333	77.46667	71.83333	64.42667	62.10000
	2	63.16087	62.15217	62.60870	56.37826	53.15652
	3	65.82581	67.44194	63.94516	61.24839	60.50645
	4	51.21875	45.86875	47.63750	44.61250	38.35000
	1	71.07857	76.90714	70.26429	63.81429	62.16429
	2	64.16667	61.36250	62.21667	56.90833	51.00833

2024	**3**	65.34063	66.10625	63.38438	60.87500	60.55313
	4	49.76000	48.22000	49.03333	49.03333	41.46000

The opportunities questions focus on employment and education prospects. Consistent with other domains, cluster 1 cities demonstrate superior performance in providing job and educational opportunities across all timeframes. This indicates robust systems and infrastructure that support career development and educational advancement, contributing to a higher quality of life and economic growth.

Cluster 4 cities, on the other hand, struggle with employment and education opportunities. This cluster's lower performance suggests challenges in creating and sustaining favorable career and educational development conditions, which could impact overall resident satisfaction and economic stability. A comparison of the average scores for 2023 and 2024 reveals that the performance in opportunities remains similar across both years.

Table 5. ***Cluster Means of the Governance Questions under the Structure Pillar for 2023 and 2024***

Year	Clusters	S_G1	S_G2	S_G3	S_G4
2023	**1**	71.07333	64.37333	52.67333	53.92667
	2	69.38261	59.62174	38.11304	46.58696
	3	66.83871	58.06129	46.12258	47.75806
	4	60.86875	47.41875	25.92500	32.02500
2024	**1**	63.93571	53.62143	54.25000	59.80000
	2	57.35000	36.43750	44.99167	51.90417
	3	57.07187	44.32812	46.79688	55.69062
	4	48.17333	28.04000	34.26000	40.32667

Governance questions evaluate aspects such as transparency in local government decisions and the level of corruption among city officials. Along with other categories, Cluster 1 demonstrates the highest performance in governance, while Cluster 4 shows the lowest performance in both years.

A comparison of governance scores between 2023 and 2024 reveals a notable decline in first and second questions in government indicators across all clusters. S_G1 (Information Accessible on Local Government Decisions) and S_G2 (Corruption of City Officials) show a marked decline from 2023 to 2024. This decline indicates a growing dissatisfaction with how accessible information about local government decisions is and a perceived increase in corruption.

The technology indicator describes the technological services and facilities accessible to locals. All domains in the structure indicator were also measured for the technology indicator. The abbreviation logic will be as described in the structure indicator. In the abbreviation T_XY, where T stands for technology, X refers to the domain, and Y stands for a number of questions. Questions about technological services and facilities in the health and safety domain, such as online reporting of city maintenance problems, free public wifi, CCTV cameras, and arranging medical appointments online are measured under the health and safety domain of technology pillar. Table 6 indicates the cluster means of the health and safety questions under the technology pillar.

Table 6. ***Cluster Means of the Health and Safety Questions under the Technology Pillar for 2023 and 2024***

Year	Clusters	T_H1	T_H2	T_H3	T_H4	T_H5	T_H6
2023	1	50.33333	60.77333	56.04667	51.24667	41.09333	66.54667
	2	51.08261	60.18696	59.94348	58.10870	51.66087	68.14783
	3	44.57742	59.46129	55.24194	49.04839	37.36129	57.04194
	4	42.48125	51.38125	49.96875	50.09375	38.31250	61.30000
	1	50.65000	60.69286	55.30714	49.21429	42.20000	65.95714
	2	49.10417	58.65417	59.01667	56.75000	50.70417	64.39167

2024	**3**	43.29688	60.11563	54.52500	49.07812	36.68750	57.31562
	4	43.99333	51.68667	50.14667	49.60667	39.86667	61.90000

Upon examining Table 6, it is evident that the performance between 2023 and 2024 is very similar. This suggests that the health indicators under the technology pillar have remained relatively stable over the two years. Cluster 2 shows better scores compared to other clusters in both years. In other words, Cluster 2 generally perform better in terms of health and safety indicators under the technology aspects. Clusters 3 and 4 present the lowest performance. However, distinguishing which cluster performs worse is challenging due to the close proximity of their scores.

Table 7. ***Cluster Means of the Mobility Questions under the Technology Pillar for 2023 and 2024***

Year	**Clusters**	**T_M1**	**T_M2**	**T_M3**	**T_M4**	**T_M5**	**T_A1**
2023	**1**	38.47333	41.72667	47.95333	68.84000	48.42000	79.28000
	2	45.53913	50.01304	52.59565	66.94348	61.00000	77.35652
	3	36.21290	39.68387	44.54516	60.70645	48.97419	74.66452
	4	35.70000	39.37500	41.68750	54.68125	54.06875	72.81250
2024	**1**	40.15000	41.87143	49.51429	69.60714	50.67143	79.23571
	2	43.78750	49.25000	52.09167	66.93750	59.11250	76.00833
	3	37.05625	39.68750	42.48438	59.40937	51.00000	74.28125
	4	35.87333	40.28667	42.26000	56.31333	53.68000	73.62000

Mobility questions encompass a range of technological and innovative practices designed to tackle various mobility challenges such as car-sharing apps, apps for available parking spaces, bicycle hiring, apps that provide real-time traffic congestion information.

Examining the cluster centers for mobility questions under the technology pillar reveals that Cluster 2 scores better than the other clusters. This indicates that cities within Cluster 2 excel in implementing technological solutions to address mobility challenges. The scores across the remaining clusters are closely aligned, exhibiting minimal variance. This reflects that the performance levels of these clusters are relatively uniform, with only slight differences in their average scores. The performance of clusters in both 2023 and 2024 is quite similar, indicating stable conditions in terms of mobility across the two years.

In the activities category, there is only one question, which pertains to how online purchasing of tickets for shows and museums makes attendance easier. The cluster mean for the activities question is high across all clusters for each year. This suggests that accessing online tickets for cultural and recreational activities, such as shows and museums, is notably convenient in the OECD cities represented.

Table 8. ***Cluster Means of the Activities and Opportunities Questions under the Technology Pillar for 2023 and 2024***

Year	Clusters	T_O1	T_O2	T_O3	T_O4
2023	1	70.21333	58.48667	50.32667	71.07333
	2	67.31739	57.54783	54.49565	69.38261
	3	68.84839	52.03226	46.80645	66.83871
	4	62.30625	44.48125	47.68750	60.86875
2024	1	69.93571	57.92857	49.92143	71.61429
	2	67.25000	56.48750	52.90000	70.10833
	3	68.70937	51.38438	46.51250	66.48750
	4	60.99333	44.64667	46.85333	59.58000

Table 8 illustrates that the results for the "opportunities" domain reveal some key insights. Questions related to online job listings, T_O1, and the quality of internet services, T_O4, have high average scores comparing other questions for each year. This indicates that access to job opportunities and the reliability of internet services are generally satisfactory across the cities.

However, the lower average scores for questions about the teaching of IT skill in the schools, T_O2, and the impact of online city services on starting new businesses, T_O3, suggest room for improvement.

Performance trends between 2023 and 2024 show close alignment, with the first cluster showing relatively better performance while the fourth cluster lags behind. This indicates a degree of consistency in the evaluation but also highlights varying levels of performance across different clusters.

Table 9. ***Cluster Means of the Governance Questions under the Technology Indicator for 2023 and 2024***

Year	Clusters	T_G1	T_G2	T_G3	T_G4
2023	**1**	40.08667	47.64000	48.74667	60.84000
	2	42.91304	51.29130	52.56087	64.29130
	3	37.11935	47.99677	44.77742	53.80645
	4	30.91875	36.38750	39.43125	56.90625
2024	**1**	40.72143	48.78571	48.25000	60.10000
	2	40.35417	50.69583	51.78333	63.02917
	3	37.03437	49.19688	44.53438	54.88750
	4	32.78667	37.04000	40.19333	58.20667

When we realize the governance-related questions under the technology pillar, Cluster 2 performs better overall than other clusters, as shown in Table 9. This suggests that cities in this cluster have advanced online platforms and services that address these governance-related aspects, such as online voting and public access to city finances. The fourth cluster exhibits poorer performance based on giving indicators. This cluster faces challenges with the performance of online government services, as evidenced by lower scores on the relevant questions.

The general score for question 1 (online public access to city finances reducing corruption) is lower, indicating a diminished perception of the role of online financial transparency in combating corruption across the cities. In contrast, T_G4, processing and identification documents online reducing waiting times, has a higher score. This demonstrates that, despite challenges in other areas, cities perform better in streamlining administrative processes through online services.

4. CONCLUSION

In this paper, the perceived smart city performance of the OECD cities was categorized using the K-means clustering algorithm. Policymakers and regulators might monitor citizens' perceptions and enhance their smart city initiatives by strategically allocating resources based on performance insights, focusing on areas where they excel or need improvement.

According to the findings, cluster means of 2023 and 2024 show little change in the overall performance. The general performance across clusters has remained stable despite some variations over the two years.

When analyzing the technology and structure pillars separately, overall, cities perform better in structural domains compared to the technological domains. This indicates that while cities excel in structural aspects, they are more open to improvement in technological areas. Although both pillars are essential for a smart city, the structural domains frequently have a stronger base and more constant focus, which results in better performance than the technical pillar.

Cities in Cluster 1 exhibit superior performance across all domains within the structural pillars. This cluster shows a high level of performance in managing structural aspects of smart city infrastructure. While excelling in structural aspects, Cluster 1 cities should invest in integrating advanced technologies to complement their strong infrastructure. The close scores between Cluster 2 and Cluster 3 suggest that these clusters have similar levels of structural characteristics. Among structural domains, traffic issue has the lowest score. This underscores the urgent need for interventions and improvements in traffic management and transportation infrastructure.

Regarding technological pillars, Cluster 2 is distinguished by its strong focus on technology based on cluster means, indicating a high degree of technological integration and innovation. This suggests that Cluster 2 can utilize advanced technology to address urban challenges. The proximity of the cluster means for Cluster 1 and Cluster 3 indicates that the technological performance across these clusters is quite similar. The domain of activities stands out with the highest scores in both the structural and technology pillars. It shows that cities are particularly effective in providing access to cultural and recreational activities through both structural and technological means.

Cluster 4 comprises cities that lag behind in structural and technological advancements, showcasing more limited progress in these areas. They should address both structural and technological deficiencies through comprehensive urban development plans. This could include upgrading infrastructure, investing in technology, and enhancing service delivery across multiple domains.

This paper focuses on the OECD cities for analysis of smart city performance. This geographic focus may limit the generalizability of the findings to non-OECD cities. Different regions, especially those with varying economic, social, and technological contexts, might exhibit different patterns of smart city performance. The study relies on a single index to assess smart city performance. This approach may oversimplify the complex nature of smart city development and potentially overlook important dimensions of performance that multiple indices could capture. Different clustering or classification algorithms might reveal alternative or more nuanced groupings of smart cities that could provide additional insights.

REFERENCES

Albino, V., Berardi, U., & Dangelico, R. M. (2015). Smart Cities: Definitions, Dimensions, Performance, and Initiatives. *Journal of Urban Technology*, *22*(1), 3–21. https://doi.org/10.1080/10630732.2014.942092

Ammara, U., Rasheed, K., Mansoor, A., Al-Fuqaha, A., & Qadir, J. (2022). Smart Cities from the Perspective of Systems. *Systems*, *10*(77).

Anthopoulos, L. (2015). Defining Smart City Architecture for Sustainability. *Electronic Government and Electronic Participation*. https://books.google.com.tr/books?hl=tr&lr=&id=FWZrCgAAQBAJ&oi=fnd&pg=PA140&dq=smart+city+terminology&ots=E6ymUHkRLp&sig=rZWG2-ENp1Q4TlxCYBx-o6-rbDo&redir_esc=y#v=onepage&q=smart%20city%20terminology&f=false

Arroub, A., Zahi, B., Sabir, E., & Sadik, M. (2016). A literature review on Smart Cities: Paradigms, opportunities and open problems. *Proceedings - 2016 International Conference on Wireless Networks and Mobile Communications, WINCOM 2016: Green Communications and Networking*, 180–186. https://doi.org/10.1109/WINCOM.2016.7777211

Caird, S. (2017). City approaches to smart city evaluation and reporting: case studies in the United Kingdom. *Urban Research & Practice*, *11*(2), 159–179.

Cantuarias-Villessuzanne, C., Weigel, R., & Blain, J. (2021). Clustering of european smart cities to understand the cities' sustainability strategies. *Sustainability (Switzerland)*, *13*(2), 1–20. https://doi.org/10.3390/su13020513

Cowley, R., Joss, S., & Dayot, Y. (2018). The smart city and its publics: insights from across six UK cities. *Urban Research & Practice*, *11*(1), 53–77.

Dameri, R., & Dameri, R. P. (2013). Searching for Smart City definition: a comprehensive proposal Searching for Smart City definition: a comprehensive proposal . *International Journal of Computers & Technology*, *11*(5). https://doi.org/10.24297/ijct.v11i5.1142

Eckhoff, D., & Wagner, I. (2018). Privacy in the Smart City - Applications, Technologies, Challenges, and Solutions. *IEEE Communications Surveys and Tutorials*, *20*(1), 489–516. https://doi.org/10.1109/COMST.2017.2748998

Fakhimi, A. H., Khani, A. H., & Sardroud, J. M. (2021). Smart-city infrastructure components. *Solving Urban Infrastructure Problems Using Smart City Technologies: Handbook on Planning, Design, Development, and Regulation*, 17–54. https://doi.org/10.1016/B978-0-12-816816-5.00002-4

Hollands, R. G. (2008). Will the real smart city please stand up? Intelligent, progressive or entrepreneurial? *City*, *12*(3), 303–320. https://doi.org/10.1080/13604810802479126

Huang, K., Luo, W., Zhang, W., & Li, J. (2021). Characteristics and problems of smart city development in China. *Smart Cities*, *4*(4), 1403–1419. https://doi.org/10.3390/SMARTCITIES4040074

IESE. (2019). *IESE Cities in Motion Index 2019*. https://blog.iese.edu/cities-challenges-and-management/2019/05/10/iese-cities-in-motion-index-2019/

IMD. (2023). *IMD-SUTD Smart City Index (SCI)*. 133.

IMD. (2024). *IMD Smart City Index 2024*.

Kenger, O. N., Kenger, Z. D., Ozceylan, E., & Mrugalska, B. (2023). Clustering of Cities Based on Their Smart Performances: A Comparative Approach of Fuzzy C-Means, K-Means, and K-Medoids. *IEEE Access*, *11*, 134446–134459. https://doi.org/10.1109/ACCESS.2023.3333753

Khan, A., Aslam, S., Aurangzeb, K., Alhussein, M., & Javaid, N. (2022). Multiscale modeling in smart cities: A survey on applications, current trends, and challenges. *Sustainable Cities and Society*, *78*. https://doi.org/10.1016/J.SCS.2021.103517

Kodinariya, T. M., & Makwana, P. R. (2013). Review on determining number of Cluster in K-Means Clustering. *International Journal of Advance Research in Computer Science and Management Studies*, *1*(6), 90–95.
Kondepudi, S., & Kondepudi, R. (2019). What Constitutes a Smart City? In *Smart Cities and Smart Spaces* (pp. 1–29). IGI Global. https://doi.org/10.4018/978-1-5225-7030-1.CH001
Lau, B. P. L., Marakkalage, S. H., Zhou, Y., Hassan, N. U., Yuen, C., Zhang, M., & Tan, U. X. (2019). A survey of data fusion in smart city applications. *Information Fusion*, *52*, 357–374. https://doi.org/10.1016/J.INFFUS.2019.05.004
Mattoni, B., Pompei, L., Losilla, J. C., & Bisegna, F. (2020). Planning smart cities: Comparison of two quantitative multicriteria methods applied to real case studies. *Sustainable Cities and Society*, *60*, 102249. https://doi.org/10.1016/J.SCS.2020.102249
OECD. (2019). *ENHANCING THE CONTRIBUTION OF DIGITALISATION TO THE SMART CITIES OF THE FUTURE*.
OECD. (2020a). *MEASURING SMART CITIES' PERFORMANCE*.
OECD. (2020b). *MEASURING SMART CITIES' PERFORMANCE*.
OECD. (2020c). *Smart Cities and Inclusive Growth*.
OECD. (2021). *TRUST IN GLOBAL COOPERATION: THE VISION FOR THE OECD FOR THE NEXT DECADE*.
OECD. (2023). *OECD Roundtable on Smart Cities and Inclusive Growth*.
Petritoli, E., Leccese, F., Pizzuti, S., & Pieroni, F. (2019). Smart lighting as basic building block of smart city: An energy performance comparative case study. *Measurement*, *136*, 466–477. https://doi.org/10.1016/J.MEASUREMENT.2018.12.095
Sancino, A., & Hudson, L. (2020). Leadership in, of, and for smart cities – case studies from Europe, America, and Australia. *Https://Doi.Org/10.1080/14719037.2020.1718189*, *22*(5), 701–725. https://doi.org/10.1080/14719037.2020.1718189
Sharma, C., Sharma, S. K., & Gill, D. (2023). Reassessing smart city components: An overview of the dynamic nature of smart city concept. *IOP Conference Series: Earth and Environmental Science*, *1186*(1). https://doi.org/10.1088/1755-1315/1186/1/012017
Simonofski, A., Vallé, T., Serral, E., & Wautelet, Y. (2021). Investigating context factors in citizen participation strategies: A comparative analysis of Swedish and Belgian smart cities. *International Journal of Information Management*, *56*, 102011. https://doi.org/10.1016/J.IJINFOMGT.2019.09.007
Sinaga, K. P., & Yang, M. S. (2020). Unsupervised K-means clustering algorithm. *IEEE Access*, *8*, 80716–80727. https://doi.org/10.1109/ACCESS.2020.2988796
United Nations Department of Economic and Social Affairs. (2024). *World Population Prospects 2024: Summary of Results*.

APPENDIX A. QUESTIONS IN IMD SMART CITY INDEX

Structures	Technology
Health & Safety	***Health & Safety***
Basic sanitation meets the needs of the poorest areas	Online reporting of city maintenance problems provides a speedy solution
Recycling services are satisfactory	A website or App allows residents to easily give away unwanted items
Public safety is not a problem	Free public wifi has improved access to city services
Air pollution is not a problem	CCTV cameras has made residents feel safer
Medical services provision is satisfactory	A website or App allows residents to effectively monitor air pollution
Finding housing with rent equal to 30% or less of a monthly salary is not a problem	Arranging medical appointments online has improved access
Mobility	**Mobility**
Traffic congestion is not a problem	*Car-sharing Apps have reduced congestion*
Public transport is satisfactory	*Apps that direct you to an available parking space have reduced journey time*
	Bicycle hiring has reduced congestion
	Online scheduling and ticket sales has made public transport easier to use
	The city provides information on traffic congestion through mobile phones
Activities	***Activities***
Green spaces are satisfactory	*Online purchasing of tickets to shows and museums has made it easier to attend*
Cultural activities (shows, bars, and museums) are sati	
Opportunities (Work & School)	***Opportunities (Work & School)***
Employment finding services are readily available	*Online access to job listings has made it easier to find work*
Most children have access to a good school	*IT skills are taught well in schools*
Lifelong learning opportunities are provided by local institutions	*Online services provided by the city has made it easier to start a new business*
Businesses are creating new jobs	*The current internet speed and reliability meet connectivity needs*
Minorities feel welcome	
Governance	***Governance***
Information on local government decisions are easily accessible	*Online public access to city finances has reduced corruption*
Corruption of city officials is not an issue of concern	*Online voting has increased participation*
Residents contribute to decision making of local government	*An online platform where residents can propose ideas has improved city life*
Residents provide feedback on local government projects	*Processing Identification Documents online has reduced waiting times*

Questions are taken from IMD (2024)

Paper #39

Title: The Future of Workplace Training: AI Avatars, Learning Outcomes, and Gender Effects

Author(s): Murathan Akhan and Aysun Bozanta

Abstract:
This paper examines the impact of AI-generated avatars on workplace training outcomes, with a focus on the role of the avatar and participant gender. Using generative AI tools like ChatGPT and Synthesia, the authors created standardized training videos and conducted controlled experiments. Results reveal that gender dynamics influence learning effectiveness, with notable differences in how participants respond to male and female avatars. The findings highlight important design considerations for AI-powered corporate education.

Keywords: AI Avatars, Workplace Training, Gender Effects, Generative AI, Learning Outcomes

Paper #52

Title: Examining the Relationship Between Artificial Intelligence and Employment in the Tourism Sector

Author(s): Taner Turgut, Muhammed Doğramacı, Selis Güler Siler and Büşra Alma Çallı

Abstract:
This paper investigates the effects of artificial intelligence (AI) on employment within the tourism sector. Through a detailed literature review and expert interviews, the study explores how AI-driven automation, chatbots, and data analytics are reshaping job structures, creating new roles while rendering others obsolete. The authors emphasize the importance of strategic planning and workforce reskilling to ensure a sustainable and inclusive digital transformation in tourism.

Keywords: Artificial Intelligence, Employment, Tourism, Digital Transformation, Workforce Adaptation
Let me know when you're ready for the next one!

Paper #61

Title: Unveiling Cultural Heritage Perceptions: A CES-Based NLP and Machine Learning Analysis of Visitor Experiences at Topkapı Palace

Author(s): Cemal Yüksel and Yasin Erduran (Sakarya University)

Abstract:
This study employs Natural Language Processing (NLP) and Machine Learning to analyze over 7,000 Google reviews of Istanbul's Topkapı Palace. Using the Cultural Ecosystem Services (CES) framework, the authors extract insights into how visitors perceive historical and cultural value. Results highlight key themes such as education, aesthetics, and spiritual enrichment, contributing to improved heritage management and visitor experience strategies.

Keywords: Cultural Heritage, Natural Language Processing, Machine Learning, Topkapı Palace, Cultural Ecosystem Services

Unveiling Cultural Heritage Perceptions: A CES-Based NLP and Machine Learning Analysis of Visitor Experiences at Topkapı Palace

Abstract

Cultural heritage sites are not only places that bear the traces of the past, but also assume important functions in terms of social identity, aesthetic experience and touristic value. This study uses large-scale text mining, sentiment analysis and machine learning techniques to analyse visitor experiences within the framework of Cultural Ecosystem Services (CES). A total of 28,706 visitor reviews were collected from Google Reviews and TripAdvisor platforms, categorized into CES categories using Zero-Shot Text Classification (ZSTC), and classified with a soft voting ensemble model. While the accuracy rate of the model was calculated as 87.6%, the most successful individual model was NuSVC, which stood out with 90.9% precision and 83.8% recall values. The findings show that visitor experiences are largely shaped around neutral (52.8%) and happy (32.3%) emotions. The categories of Recreational, Religion and Culture received the highest positive feedback; the History and Architecture categories had rather higher degrees of astonishment and melancholy. The low degrees of negative emotions imply that visitors of cultural heritage sites find them to be an appealing experience. This study provides important insights for cultural heritage managers, tourism planners and policy makers. Unlike traditional CES assessment methods, it shows that machine learning and artificial intelligence-based big data analytics offer a systematic and scalable perspective in cultural heritage management. The findings of the study contribute to the integration of sustainable tourism strategies and cultural heritage policies into data-driven decision-making processes.

Keywords: Cultural Ecosystem Services, Sentiment Analysis, Machine Learning, Zero-Shot Text Classification, Cultural Heritage Management

1 INTRODUCTION

Cultural heritage sites are considered as elements that shape the collective memory of societies and are of great historical, artistic and architectural significance. However, these sites are not only a reminder of the past, but also a key component of social and economic development. The conservation and sustainable management of cultural heritage has become an important component of the tourism sector, and the study of visitor experiences and perceptions through scientific methods is a critical requirement for a better understanding of the social value of these sites. In this context, the concept of CES provides a holistic framework that defines the intangible benefits that individuals derive from cultural heritage sites, and provides the opportunity to systematically assess the social value of these sites.

Cultural heritage monuments not only offer historical knowledge but also enable individuals to feel physically belonging by means of aesthetic, spiritual, and recreational experiences (Chang et al., 2020; Russell et al., 2013). The CES framework provides a methodical approach to understand the intangible benefits emerging from interactions between humans and their environment as well as their legacy sites (Keniger et al., 2013).

Reviewing the literature demonstrates that traditionally surveys, interviews, and expert opinions have formed the foundation for CES assessments (Stephenson et al., 2020; Torralba et al., 2020). However, data science techniques include natural language processing (NLP) and large-scale text analysis enable one to undertake more thorough and in-depth investigations for the evaluation of CES as digitalization speeds up.

Especially on internet platforms, visitor comments and social media content are a valuable source of data for research of the impact of cultural legacy sites. Still, meticulously examining such enormous and unstructured data requires more sophisticated data processing techniques than traditional ones Deep learning-based sentiment analysis models and artificial intelligence techniques such ZSTC enable highly accurate classification of visitors' perceptions of cultural heritage sites from a CES perspective, the application of which is growing relevance in large-scale studies in this context.

This study aims to evaluate visitor experiences towards Topkapı Palace, one of the most important cultural heritage sites of Istanbul, within the framework of CES. The 28,997 visitor reviews collected from online platforms (TripAdvisor, Google Reviews) were first classified into CES categories using the ZSTC technique. Then, a threshold value was set and detailed analyses were performed on the data with high accuracy scores and the model was trained with various machine learning algorithms. This process allowed for a more reliable identification of the different components within the CES framework and a more statistically sound basis for visitor experiences. At the same time, sentiment analysis was applied to evaluate visitors' perceptions of aesthetic values, cultural-historical heritage, educational and historical awareness, recreational experiences and spiritual-religious ties in detail.

By proving the relevance of sentiment analysis and text classification techniques in CES evaluations, this work intends to offer particular recommendations for cultural heritage management and sustainable tourism strategy. From a data-driven point of view, understanding of how cultural legacy monuments affect tourist experiences can direct projects of cultural heritage management and tourism. This paradigm gives managers and legislators significant ramifications regarding the efficient use of tourist data and preservation of cultural legacy.

2 LITERATURE REVIEW

For the intangible benefits ecosystems offer for people, CES characterizes their engagement with the surroundings and culture. All very significant for how people interpret and interact with cultural legacy, these benefits include aesthetic appreciation, spiritual enrichment, leisure activities, identity development, and traditional knowledge. Since the 2005 Millennium Ecosystem Assessment, studies on ecosystem services have made increasingly use of CES. Still under research is its interaction with other ecosystem services, particularly those pertaining to provision and control.

Despite its significance, CES remains largely underrepresented in academic research, with only 2% of ecosystem services studies focusing on cultural heritage, whereas 75% prioritize environmental and ecological aspects. According to UNESCO, cultural landscapes serve as primary interfaces between CES and cultural heritage, encompassing both tangible elements (e.g., historic structures, archaeological sites) and intangible attributes (e.g., local traditions, spiritual values. For CES, tourism is thus rather important since it fosters local identity and cultural sustainability. Emphasizing the requirement of community-driven policies that conserve social and cultural values instead of merely stressing economic incentives, field studies in rural Hungary illustrate how CES helps to establish local identity and tourist increase.

As tourism sustainability becomes more important, CES is seen as both enhancing geographical appeal and being responsive to too high visitor counts. While poor management runs the risk of jeopardizing cultural services, well-run tourism helps to preserve them. These days, big data analysis changing public opinions regarding CES research incorporates GIS mapping, visitor comments, and social media insights. Recent research underline the practical applications of CES in heritage management, so offering data for the development of sustainable plans balancing community well-being, increase of tourism, and protection of cultural legacy.

Table 1. CES in Research: A Comparative Overview of Key Studies and Methodologies

Study	Findings	Results	Theories	Context	Methodology
(Ferguson et al., 2024)	CES exhibits strong associations with visitor loyalty and intention to return. 'Education' and "sense of belonging" are the factors that most influence visitor loyalty. Intention to recommend is the variable that most influences visitors' intention to return.	Park managers can strengthen long-term visitor loyalty by investing in visitor education and sense of belonging programmes. CES factors play a critical role in shaping visitor behaviour.	Social-Ecological Systems (SES) framework	Great Bay National Estuarine Research Reserve (GBE), ABD	Questionnaire survey (645 participants), Structural Equation Modelling (SEM)
(Tew et al., 2019)	Forest management directly affects CES. Areas valued by people were identified with participatory GIS method. Increasing tree diversity and protecting open spaces in forest management can positively affect the visitor experience.	Decision makers in forest management should make the forest structure more diverse to increase CES and consider open areas in management.	CES Framework, Social-Ecological Systems	Thetford Forest, United Kingdom	Participatory GIS analysis, Area matching technique
(Richards & Friess, 2015)	Content analysis of geo-tagged photos on Flickr can provide fast and low-cost data on CES. The most common photo categories were nature observation, landscape and social recreation.	Social media data can be used as an effective and fast method to evaluate ecosystem services. With spatial analysis, detailed information about the activities of visitors can be obtained and management strategies can be shaped accordingly.	Ecosystem Services Framework, Spatial Ecological Analysis	Four different mangrove areas in Singapore	Social media data analysis, Content analysis, MaxEnt modelling
(McElwee, Vũ, et al., 2022)	CES varies over time and includes both material and immaterial elements. Agricultural production,	Sustainable management of CESs should take into account local identity and historical context. Policies should be	CES Framework, Social-Ecological Systems	North Central Vietnam, especially the Hà Tĩnh region	Longitudinal study, Surveys, Participant

	traditional medicinal plants and handicrafts are closely linked to cultural identity and sense of belonging. The migration of younger generations in the region has reduced the utilisation of traditional ecosystem services.	geared towards protecting both the tangible and intangible components of ecosystem services. Social variables such as migration greatly influence CES utilisation.			observation, In-depth interviews
(Selfa et al., 2021)	The expansion of eucalyptus plantations has led to the loss of former agricultural land and natural habitat, changing place attachment and perceptions of ecosystem services. Impacts on water resources and landscapes shape local people's perceptions, with migrating communities adapting to new economic opportunities, while settled groups view ecosystem changes more negatively.	Place attachment is a critical factor in adapting to socio-ecological changes. Policy makers should develop sustainable land management strategies, taking into account local people's perceptions and CES.	CES, Place Attachment Theory	Ubajay, Entre Ríos, Argentina	In-depth interviews (34 people), Participant mapping, Spatial analysis
(Sultana & Selim, 2021)	Participants find the CES offered by urban green spaces important. Recreation, aesthetic values and sense of belonging are the most prominent CES categories. While the use of green spaces varies according to the social, economic and demographic characteristics of individuals, roof gardens and green parks are seen as the most valuable areas.	Urban green space management should focus on the needs of local people to increase social participation and emphasise the importance of CES. Policy makers should support efforts to protect and expand green spaces with community-based management models. The co-operation of individuals and the state is critical for CES management.	CES, Sustainable City Management	Dakka, Bangladeş	Survey-based preference method, Descriptive and inferential statistical analyses

(Hunter & Lauer, 2021)	Fishermen place more emphasis on subsistence fishing and scientists place more emphasis on habitat conservation. Photo-assisted surveys did not fully reflect the relationship with ecosystem services. All stakeholders have common concerns about the contribution of economic activities to environmental degradation.	The assessment of CES can be more effective through participatory research methods. Since the ES framework is based on the nature-culture distinction, it may not fully reflect the relationship of some communities with the ecosystem. Therefore, ES research needs to be more flexible and contextualised.	CES, Nature-Culture Dilemma	Moorea, Fransız Polinezyası	Photo elicitation, mixed methods (quantitative and qualitative), field observation
(He & Guo, 2021)	The integration of CES into conservation efforts plays an important role in both ecological conservation and in meeting the cultural and spiritual needs of local people. Local cultural practices and religious rituals should not be overlooked in CES assessments.	The effectiveness of conservation policies is enhanced when they are integrated with local culture and traditions. Policy makers should develop participatory methods for the inclusion of CES in ecosystem management and planning.	CES, Protection Policies	Pudacuo National Park, Tibet Region, Southwest China	Case study
(Kosanic & Petzold, 2020)	The impacts of CES on human welfare need to be further investigated. Most studies are concentrated in Europe and North America, while studies in the Global South are scant. The effects of CES on physical and mental health are often discussed in generalised terms and cause-effect relationships are not clearly stated.	More regional and interdisciplinary research is needed to better understand the relationships between CES and human well-being. In particular, the CES experiences of disadvantaged communities, persons with disabilities and vulnerable groups should be explored. The integration of CES into policy and protection planning should be given more consideration.	CES, Human Wellbeing Framework	Global scale (different countries and communities; geographical trends were assessed in the review)	Systematic literature review

Recent studies on the usage of CES in environmental management, cultural legacy preservation, and tourist policy have looked on its relevance (Selfa et al., 2021; McElwee et al., 2022). Although CES transcends biophysical facts to affect social belonging, identity, and spatial context, major variations still exist in how its intangible features are measured and applied into policy decisions. He and Guo (2021) show how even if local cultural activities are sometimes disregarded, CES is included into protected area management. The 2020 systematic review by Kosanic and Petzold highlights the need of more comprehensive, data-driven research since it indicates comparable spatial differences in CES research.

Advancement of CES studies need massive data analytics, artificial intelligence, and social media analysis. Studies by Ferguson et al. (2024) and Tew & Simmons (2019) show how CES affects visitor involvement and landscape management; Richards & Friess (2015) and Chen et al. (2024) show how GIS and AI-supported technologies increase data-driven decision-making. Though interesting, CES tests have not yet fully accepted ZSTC, a text classification free of historical data (Yin et al., 2019). Chen et al. (2024) speculate on how text mining and machine vision could look at CES impressions in urban parks, thereby tying visitor experiences with leisure activities and visual interactions.

ZSTC and sentiment analysis study of 28,706 visitor reviews of Topkapı Palace enables this endeavor narrow the methodological gap in CES research. By means of closely classifying visitor narratives inside the CES framework, this research offers insights on tourist policy, cultural legacy management, and the greater convergence of CES and NLP (Nawowicz et al., 2024; Yarlagadda & al., 2024). The results emphasize the increasing importance of artificial intelligence and big data for study of cultural legacy and improvement of strategic decision-making.

3 METHODOLOGY

The overall methodology of this study is illustrated in Figure 1, which presents a structured workflow of the research process, covering data collection, pre-processing, classification, sentiment analysis, and ML-based categorization of visitor experiences within the CES framework. The approach integrates NLP, ZSTC, and supervised ML techniques to systematically evaluate and classify visitor reviews from Google Reviews and TripAdvisor regarding Topkapı Palace.

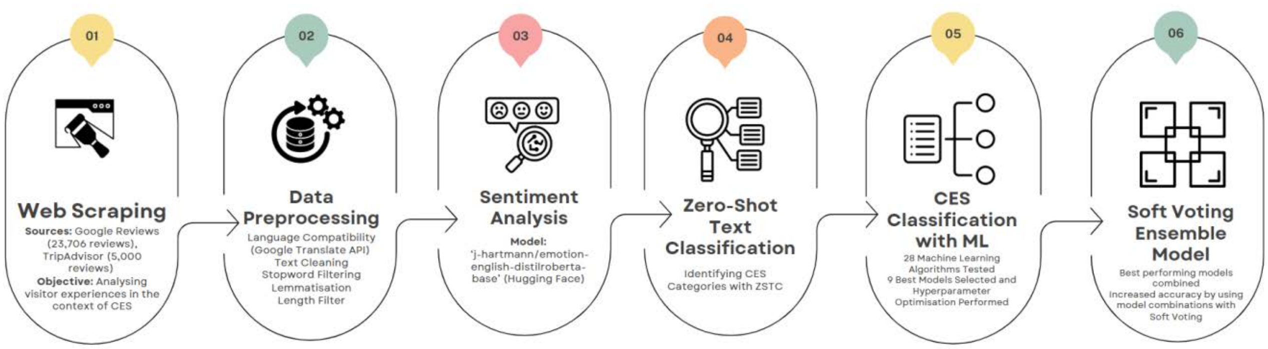


Figure 1. The overall methodology of this study

The first stage was data collecting using web scraping; TripAdvisor (5,000) and Google Reviews (23,706) produced 28,706 visitor reviews. The Google Translator API translated non-English comments into English in order to guarantee linguistic uniformity. Raw text data then obtained NLP-based pre-processing involving removal of special characters, punctuation, stopwords, lemmatization, and length filtering, therefore guaranteeing a refined dataset for further research.

Sentiment analysis made advantage of the Hugging Face "j-hartmann/emotion- English-distilroberta-base" model. Every assessment revealed the general attitude, which this method found to be either favorable, negative, or neutral and also indicated particular emotions such grief, rage, and happiness. This emotional profile made possible more complete information of visitor experiences by means of a dual-layer analysis combining sentiment evaluation with CES classification.

Using ZSTC for CES classification, automatic classification free of pre-trained labels (Yin, Hay & Roth, 2019) was obtained. ZSTC gave relevant remarks major priority for hand annotations instead of assigning labels straight forwardly. The balanced final dataset had 500 positive and 500 negative samples per CES category, so improving ML training.

Table 2. CES Label Distribution and Average Score ZSTC

CES Label	Count	Score
Cultural	17471	0.56
Architecture	3541	0.46
History	2487	0.53
Recreational	4520	0.46
Religion	396	0.46

The supervised ML phase evaluated 28 different methods in search of the best classifiers for CES classification. Feature extraction made use of TF-IDF, accentuating key phrases to reduce the impact of low-information terms and so enhance text vectorization (Ramos, 2003). Model performance was assessed among other factors using K-fold cross-valuation for accuracy, precision, recall, and F1-score. The top nine models were hyperparameter adjusted for yet more development.

One increased classification dependability by using an ensemble learning approach. Combining into a soft voting ensemble model, the top-performing models made advantage of the combined predictive power of many classifiers. This approach considerably improved classification accuracy and resilience as well as offered a scalable, data-driven approach of CES-related visitor experience research.

4 FINDINGS

In this section, the performance results of the supervised machine learning models applied to classify visitor comments in the CES framework are presented in detail. In the modelling process, the effectiveness of each model was compared using common classification metrics such as accuracy, precision, recall and F1 score. In order to evaluate the model performances more reliably, k-fold cross-validation method was applied to increase the generalisation ability of the models and minimise the risk of overlearning. In this study, 28 different machine learning models were tested and the performance of each model in CES classification was analysed. Table 3 shows the comparison of the models according to average performance metrics:

Table 3. Comparison of Average Performance Metrics Across Different Models

Model	Accuracy	Precision	Recall	F1-Score
AdaBoost	0.755	0.760	0.784	0.759
Bagging Classifier	0.822	0.807	0.848	0.826
BernoulliNB	0.817	0.742	0.979	0.843
CatBoost	0.844	0.833	0.868	0.848
ComplementNB	0.870	0.852	0.898	0.874
Decision Tree	0.788	0.779	0.807	0.791
Extra Tree	0.750	0.733	0.788	0.759
Extra Trees	0.870	0.874	0.868	0.870
GaussianNB	0.805	0.813	0.793	0.802
Gradient Boosting	0.805	0.795	0.840	0.811
Hist Gradient Boosting	0.819	0.808	0.839	0.822

KNN (k=5)	0.704	0.764	0.657	0.626
LDA	0.777	0.764	0.801	0.781
LightGBM	0.811	0.803	0.825	0.813
Linear SVC	0.873	0.878	0.869	0.873
Logistic Regression	0.860	0.882	0.836	0.857
Naive Bayes	0.870	0.852	0.899	0.874
NuSVC	0.876	0.909	0.838	0.871
Passive Aggressive Classifier	0.856	0.843	0.884	0.861
Perceptron	0.837	0.860	0.821	0.833
QDA	0.653	0.861	0.358	0.495
Random Forest	0.856	0.855	0.860	0.856
Ridge Classifier	0.874	0.883	0.863	0.873
SGD Classifier	0.860	0.856	0.871	0.862
SVM (linear)	0.867	0.875	0.858	0.866
SVM (poly)	0.782	0.972	0.581	0.724
SVM (rbf)	0.873	0.917	0.822	0.866
XGBoost	0.835	0.834	0.839	0.835

Among the 28 various machine learning models examined as a result of the experimental analyses, NuSVC (0.876), Ridge Classifier (0.8874), Linear SVC (0.873), Extra Trees (0.870), ComplementNB (0.870) and Naive Bayes (0.870) had the greatest accuracy in terms of CES classification. On the decomposition of CES categories, these models showed great generalization ability, and on the dataset they yielded good results.

Particularly NuSVC (accuracy = 0.876, precision = 0.909, recall = 0.838, F1-score = 0.871) model displayed the best accuracy. While the rather low recall value suggests that some CES categories are not completely covered, the great precision value of this model indicates that the classifications of CES categories are essentially accurate.

Likewise, the Ridge Classifier (accuracy = 0.874, precision = 0.843, recall = 0.863, F1-score = 0.873) and Linear SVC (accuracy = 0.873, precision = 0.878, recall = 0.869, F1-score = 0.873) models also stood out as good substitutes in CES evaluations.

With the SVM (poly) model, the SVM (poly) model (precision = 0.972) got greatest success in terms of the precision metric. This model's recall value, 0.581, was noted to be weak in terms of covering a broad spectrum of CES categories though. This suggests that although under-predicts some categories, the model achieves great-precision categorization.

By contrast, the BernoulliNB (recall = 0.979) model displayed the best result in the recall measure. Still, this model had 0.742 for precision and 0.817 for accuracy respectively. These findings show that although the model can forecast high coverage rate CES categories, the false positive rate is also somewhat significant.

The most successful models according to F1-score were ComplementNB (accuracy = 0.870, precision = 0.852, recall = 0.898, F1-score = 0.874), Naive Bayes (accuracy = 0.870, precision = 0.852, recall = 0.899, F1-score = 0.874) and Extra Trees (accuracy = 0.870, precision = 0.874, recall = 0.868, F1-score = 0.870). These models produced consistent results in CES classifications with the best balance between precision and recall.

In order to further optimise the performance of the machine learning models, hyperparameter optimisation was performed on the NuSVC, Ridge Classifier, Linear SVC, ComplementNB, Naive Bayes, Extra Trees, AdaBoost, Hist Gradient Boosting and Random Forest models that produced the best results. In the optimisation process performed with the Grid Search method, the most appropriate parameters for each model were determined and improvements in prediction accuracy rates were achieved as a result of retraining with these parameters.

In the final stage, the ensemble learning method was applied by combining the most successful models obtained and a soft voting based meta-model was created. This process allowed to increase the accuracy of CES classification by exploiting the strengths of different models and improved the generalisation capability of the model. Table 4 shows the average performance metrics of the Soft Voting Ensemble Model for different CES categories:

Table 4. Average Performance Metrics of the Soft Voting Ensemble Model

CES Category	Accuracy	Precision	Recall	F1-Score
Religion	0.924	0.933	0.915	0.923
Recreational	0.901	0.906	0.894	0.900
Culture	0.875	0.871	0.882	0.876
Architecture	0.869	0.883	0.852	0.867
History	0.867	0.865	0.878	0.870

The soft voting ensemble model achieved higher accuracy rates compared to the individual machine learning algorithms. Table 5 shows the performance comparison between NuSVC, the most successful single model, and the soft voting ensemble model:

Table 5. Comparison of Soft Voting Ensemble Model and Best Individual Model

Model	Accuracy	Precision	Recall	F1-Score
Best Individual Model (NuSVC)	0.884	0.909	0.838	0.871
Soft Voting Ensemble	0.895	0.903	0.875	0.889

The results show that the soft voting ensemble model achieves better accuracy rates than the best single model (NuSVC). In addition, a significant improvement was observed in Precision, Recall and F1-Score values.

The findings show that machine learning-based analyses can be applied with high accuracy in the process of categorising visitor experiences within the framework of CES. Important methodological contributions to the integration of sustainable tourist policies and cultural heritage management into data-driven decision-making procedures are given by this work. Moreover, it has been shown that more methodical evaluation of the intangible aspects of CES is made possible by large-scale data studies including natural language processing and deep learning approaches.

According to the classification results of the ensemble model, the History category had the widest coverage with 12,379 comments in the distribution of visitor comments. The Culture category ranked second with 10,825 comments, while the Architecture category ranked third with 7,958 comments. Recreational category has 7,918 comments, while Religion category has the least number of comments with 4,377 comments.

Figure 2. Distribution of Comments Across CES Categories

Figure 2 visualises the distribution of visitor comments classified by the anamble model according to CES categories. Figure 2 reveals that the History category contains the highest number of comments, while Culture and Architecture categories have a significant share. The Religion category stands out as the group with the least number of comments compared to the other categories. This distribution provides important clues about how visitors' perceptions and experiences of cultural heritage sites are shaped in different CES dimensions. In the next section, these findings will be analysed in depth and the insights offered by visitor comments within the CES framework will be discussed.

The findings indicate that tourist feedback predominantly pertains to the categories of History (12,379) and Culture (10,825), reflecting the paramount importance of these aspects of Topkapı Palace to visitors. This insight underscores the necessity for tailored management strategies that enhance tourists' cultural experiences by including historical context.

Examining the comments exposes a major issue with restricted access to some Harem sites causing visitor dissatisfaction. By increasing access to now limited sites or providing alternate interpretative experiences, solving this issue can assist to considerably increase tourist happiness. Moreover, improving the accessibility of these sites could be a re-engagement tactic, motivating past visitors to return and so raise the attraction of the site to new users.

These findings illustrate the several ways in which emotional sensitivity and language analysis might help to preserve cultural legacy. By means of meticulous review of visitor feedback, decision-makers can prioritize enhancements commensurate with public expectations, therefore fostering an engaging and immersive cultural experience. This exacting scientific technique ensures tourist connection and supports cultural heritage tourism to grow over extended times.

According to the findings of the sentiment analysis, neutral emotion was observed at the highest rate in all CES categories. This was followed by happiness, while the rates of surprise and sadness were relatively lower. On the other hand, anger, disgust and fear are among the least observed emotions, indicating that visitors tend to have a positive or neutral evaluation in general.

Table 6 presents the percentages of the distribution of emotions according to the CES categories, revealing in detail the emotions around which visitors' experiences of cultural heritage sites are shaped:

Table 6. Sentiment Distribution of Visitor Comments Across CES Categories

CES Categories	Anger	Disgust	Fear	Joy	Neutral	Sadness	Surprise
Religion	0.8%	5.4%	0.9%	32.3%	52.8%	2.6%	5.2%
Recreational	1.1%	4.3%	1.3%	33.1%	49.0%	5.0%	6.3%
Culture	1.3%	5.4%	1.3%	29.5%	50.4%	4.9%	7.1%
Architecture	1.0%	6.1%	1.2%	28.2%	49.6%	5.7%	8.2%
History	1.2%	5.7%	1.2%	25.2%	54.7%	5.0%	7.0%

Table 6 shows in percentages the range of emotions found in visitor comments according to CES categories. According to the results, in all spheres neutral sentiment rates are highest. This shows that most tourists comment on cultural heritage places using either neutral or descriptive language.

Happiness stands out as the most common emotion after neutral emotion. Especially Recreational (33.1%) and Religion (32.3%) categories contain the highest happiness rates. This finding suggests that visitors tend to develop a positive perception of their experiences with recreational and religious sites. On the other hand, the relatively lower happiness rate in the

History (25.2%) category suggests that historical places tend to influence visitors with a more informative and neutral perception.

Among the emotions, the rate of surprise was lower than the other positive emotions, but relatively higher in the Architecture (8.2%) and Culture (7.1%) categories. This indicates that architectural structures and cultural elements arouse aesthetic or unexpected admiration in visitors.

When negative emotions are analysed, it is seen that the rates of anger, disgust and fear are quite low. However, disgust was measured at relatively high levels in the Architecture (6.1%) and History (5.7%) categories compared to the other categories. This finding suggests that some visitors tend to make negative judgements about architectural or historical elements.

Finally, although sadness rates were low in all categories, they were higher in Architecture (5.7 per cent) and History (5.0 per cent) compared to the other categories. This indicates that historical and architectural elements may have a melancholic or nostalgic effect on some visitors.

Overall, the results of the sentiment analysis show that visitors' perceptions of cultural heritage sites are largely shaped around neutral and positive emotions. These data provide important insights for understanding and improving visitor experiences for cultural heritage management and tourism planning.

In order to evaluate the results of the sentiment analysis of visitor comments in a more visual way, the percentage distribution of sentiment by CES categories is presented in Figure 2. The graph represents the proportions of the main emotions observed in the comments belonging to each category, revealing in detail the emotional components of visitors' perceptions of cultural heritage sites. In particular, by analysing how emotions such as neutral, happiness, surprise and sadness vary by category, the emotion-based dynamics of visitor experiences within the CES framework are more comprehensively assessed.

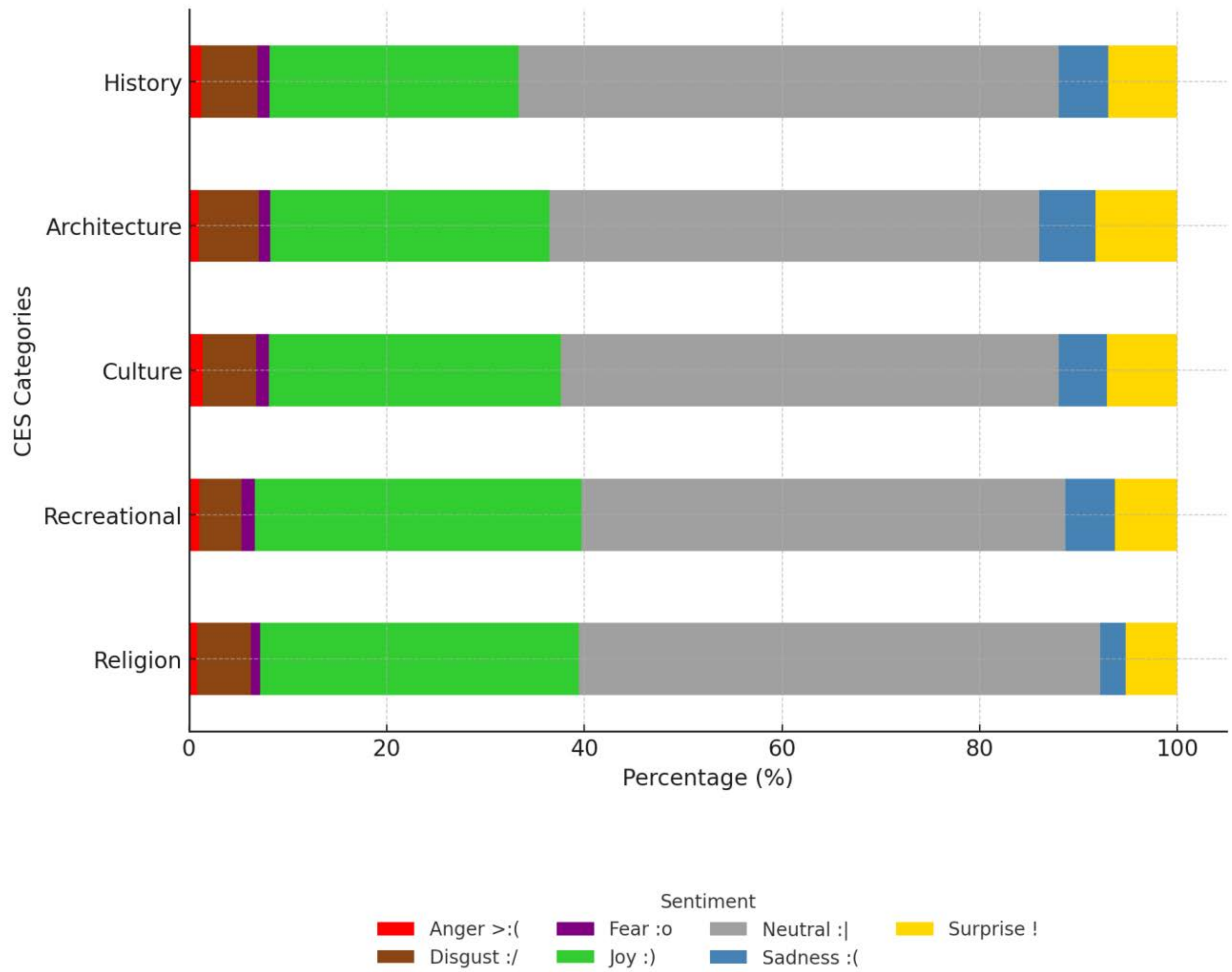


Figure 3. Percentage-Based Sentiment Analysis Results Across CES Categories

Figure 3 shows, among the CES categories, sentiment analysis percentage-based results. According to the graph, most visitors in their comments use neutral language; this pattern is observed in every type of visits. Particularly obvious in the Recreational, Religion and Culture categories are the green tones implying the gladness. This implies that guests of leisure facilities and sites bearing religious or cultural legacy often have positive experiences there.

Though their rates are lower than in other groups, in the Architecture and History category emotions like confusion (yellow) and mourning (blue) have comparatively higher frequencies. This outcome reveals how often visitors artistically and emotionally find inspiration in architectural and historical elements.

On the other hand, in all spheres negative emotions—anger, fear, and disgust expressed by red and purple tones—remained low. On the other hand, the substantially higher percentages of dissatisfaction in the categories of Architecture and History suggest that some visitors left negative remarks due of physical ambient conditions or unsatisfied expectations.

This paper shows that the CES framework lets one rigorously assess the emotional elements of visitor encounters at sites of cultural significance. The results of the sentiment analysis provide important fresh ideas for improving services in tourism management and cultural heritage planning processes as well as for understanding visitor impressions.

5 DISCUSSION, CONCLUSION AND SUGGESTIONS

In this work, large-scale analysis of visitor comments inside the framework of CES was conducted using sentiment analysis and text classification techniques integrated with NLP and machine learning methodologies. According to the results, tourists' impressions of cultural heritage places are mostly formed by neutral and positive feelings. Particularly, the finding of pleasure emotion at greater rates in Recreational, Religion, and Culture categories indicates that these sites benefit users. Conversely, architectural and historical aspects of emotions like surprise and melancholy are connected to each other, implying that cultural legacy can inspire in visitors both aesthetically and emotionally. Conversely, the low levels of negative feelings help to confirm that cultural heritage places provide a good tourism value and that visitors usually have a fulfilling experience.

The study makes one of the most significant contributions by proving how well artificial intelligence and big data analytics perform in CES assessments. Although conventional CES studies mostly rely on surveys and expert judgments, this work indicates that machine learning-based text mining techniques have the ability to objectively and methodically evaluate the intangible aspects of CES. Advanced analytical techniques are clearly applicable in CES research based on the identification of CES categories in large-scale textual data with ZSTC and the enhancement of classification accuracy with the soft voting ensemble model. With a data-driven approach, the results let cultural heritage management and sustainable tourism plans to be reshaped.

Several foundational principles can effectively guide future research directions in this field. First of all, adding visual data analytics and GIS to CES studies helps one to have a more complete knowledge of how cultural heritage sites fit visitor impressions. Second, a closer examination of sentiment analysis—that is, contrasting the experiences of local people's cultural legacy with those of various demographic groups—may help one to grasp the social consequences of CES. At last, the generalisability of the model and a larger methodological framework for CES assessments can be tested by applying the ZSTC and ensemble learning techniques utilized in this study to several cultural heritage sites. By use of such data-driven techniques, cultural heritage management will be able to transition from a just conservation-based process to a proactive tool for maximising tourist experiences and sustainable tourism initiatives.

REFERENCES

Becken, S., Stantic, B., Chen, J., Alaei, A. R., & Connolly, R. M. (2017). Monitoring the environment and human sentiment on the Great Barrier Reef: Assessing the potential of collective sensing. *Journal of Environmental Management*, 203(1), 87–97. https://doi.org/10.1016/J.JENVMAN.2017.07.007

Brindley, P., Cameron, R. W., Ersoy, E., Jorgensen, A., & Maheswaran, R. (2019). Is more always better? Exploring field survey and social media indicators of quality of urban greenspace, in relation to health. *Urban Forestry & Urban Greening*, 39(1), 45–54. https://doi.org/10.1016/J.UFUG.2019.01.015

Carrillo-Acosta, N., Alarcón-Rivera, Z., & Valderrama-López, C. F. (2024). Tendencias del turismo sostenible en sitios patrimoniales, un análisis bibliométrico. *CLIO América*, 18(35), 1–17. https://doi.org/10.21676/23897848.5664

Chang, C. C., Cheng, G. J. Y., Nghiem, T. P. L., Song, X. P., Oh, R. R. Y., Richards, D. R., & Carrasco, L. R. (2020). Social media, nature, and life satisfaction: Global evidence of the biophilia hypothesis. *Scientific Reports*, 10(1), 1–8. https://doi.org/10.1038/s41598-020-60902-w

Chen, X., Lee, T. J., & Hyun, S. S. (2025). Visitors' self-expansion and perceived brand authenticity in a cultural heritage tourism destination. *Journal of Vacation Marketing*. https://doi.org/10.1177/13567667241309122

Chen, Y., Hong, C., Yang, Y., Li, J., Wang, Y., Zheng, T., Zhang, Y., & Shao, F. (2024). Mining social media data to capture urban park visitors' perception of cultural ecosystem services and landscape factors. *Forests, 15(1)*, 213. https://doi.org/10.3390/F15010213

Csurgó, B., & Smith, M. K. (2022). Cultural heritage, sense of place and tourism: An analysis of cultural ecosystem services in rural Hungary. *Sustainability*, 14(12), 7305. https://doi.org/10.3390/SU14127305

Eisenstein, J. (2019). *Introduction to natural language processing* (Adaptive Computation and Machine Learning series). MIT Press. https://mitpress.mit.edu/books/introduction-natural-language-processing

Ferguson, M. D., Robinson, T., Ferguson, L. A., Evensen, D., Schwartz, F., Gonyo, S., & Freitag, A. (2024). Cultivating commitment: How cultural ecosystem services affect visitor loyalty attitudes and intention-to-return in parks and protected areas. *Ecosystems and People*, 20(1), 1–14. https://doi.org/10.1080/26395916.2023.2297560

Graham, L., Eigenbrod, F., Bullock, J. M., & Parks, K. E. (2021). Enriching social media data allows a more robust representation of cultural ecosystem services. *Ecosystem Services*, 50, 101328. https://doi.org/10.1016/J.ECOSER.2021.101328

Havinga, I., Bogaart, P. W., Hein, L., & Tuia, D. (2020). Defining and spatially modelling cultural ecosystem services using crowdsourced data. *Ecosystem Services*, 43, 101091. https://doi.org/10.1016/J.ECOSER.2020.101091

Havinga, I., Marcos, D., Bogaart, P., Tuia, D., & Hein, L. (2024). Understanding the sentiment associated with cultural ecosystem services using images and text from social media. *Ecosystem Services*, 65, 101581. https://doi.org/10.1016/J.ECOSER.2023.101581

He, J., & Guo, N. (2021). Culture and parks: Incorporating cultural ecosystem services into conservation in the Tibetan region of Southwest China. *Ecology and Society*, 26(3), 12. https://doi.org/10.5751/ES-12572-260312

Hølleland, H., Skrede, J., & Holmgaard, S. B. (2017). Cultural heritage and ecosystem services: A literature review. *Conservation and Management of Archaeological Sites*, 19(3), 210–237. https://doi.org/10.1080/13505033.2017.1342069

Huai, S., & Van de Voorde, T. (2022). Which environmental features contribute to positive and negative perceptions of urban parks? A cross-cultural comparison using online reviews and natural language processing methods. *Landscape and Urban Planning*, 218, 104307. https://doi.org/10.1016/J.LANDURBPLAN.2021.104307

Hunter, C. E., & Lauer, M. (2021). Ecosystem services research in action: Reflexively valuing environments in the South Pacific. *Ecology and Society*, 26(2). https://doi.org/10.5751/ES-12253-260224

Keniger, L. E., Gaston, K. J., Irvine, K. N., & Fuller, R. A. (2013). What are the benefits of interacting with nature? *International Journal of Environmental Research and Public Health*, 10(3), 913. https://doi.org/10.3390/IJERPH10030913

Kosanic, A., & Petzold, J. (2020). A systematic review of cultural ecosystem services and human wellbeing. *Ecosystem Services*, 45, 101168. https://doi.org/10.1016/j.ecoser.2020.101168

Lazarev, L. (2024). Cultural memory as the foundation of European identity. *Studiul Artelor Și Culturologie: Istorie, Teorie, Practică,* 1(46), 123–127. https://doi.org/10.55383/AMTAP.2024.1.18

McElwee, P., He, J., & Hsu, M. (2022). Challenges to understanding and managing cultural ecosystem services in the global South. *Ecology and Society*, 27(3). https://doi.org/10.5751/ES-13427-270323

McElwee, P., Vũ, H., Võ, G., & Lê, D. (2022). Patriotism, place, and provisioning: Assessing cultural ecosystem services through longitudinal and historical studies in Vietnam. *Ecology and Society*, 27(1). https://doi.org/10.5751/ES-12615-270103

Nawawi, I., Ilmawan, K. F., Maarif, M. R., & Syafrudin, M. (2024). Exploring tourist experience through online reviews using aspect-based sentiment analysis with zero-shot learning for hospitality service enhancement. *Information*, 15(8), 499. https://doi.org/10.3390/INFO15080499

Ramos, J. (2003). Using TF-IDF to determine word relevance in document queries. Proceedings of the First Instructional Conference on Machine Learning.

Richards, D. R., & Friess, D. A. (2015). A rapid indicator of cultural ecosystem service usage at a fine spatial scale: Content analysis of social media photographs. *Ecological Indicators*, 53, 187–195. https://doi.org/10.1016/J.ECOLIND.2015.01.034

Russell, R., Guerry, A. D., Balvanera, P., Gould, R. K., Basurto, X., Chan, K. M. A., Klain, S., Levine, J., & Tam, J. (2013). Humans and nature: How knowing and experiencing nature affect well-being. *Annual Review of Environment and Resources*, 38, 473–502. https://doi.org/10.1146/ANNUREV-ENVIRON-012312-110838

Selfa, T., Marini, V., & Abrams, J. B. (2021). Place attachment and perceptions of land-use change: Cultural ecosystem services impacts of eucalyptus plantation expansion in Ubajay, Entre Ríos, Argentina. *Ecology and Society,* 26(4). https://doi.org/10.5751/ES-12870-260444

Stephenson, L. B., Harel, A., Rubenson, D., & Loewen, P. J. (2020). 2019 Canadian Election Study (CES) - Online Survey. *Canadian Election Study Database*. https://doi.org/10.7910/DVN/DUS88V

Sultana, R., & Selim, S. A. (2021). Residents' perceptions of the role and management of green spaces to provide cultural ecosystem services in Dhaka, Bangladesh. *Ecology and Society*, 26(4). https://doi.org/10.5751/ES-12656-260405

Taecharungroj, V., & Mathayomchan, B. (2019). Analysing TripAdvisor reviews of tourist attractions in Phuket, Thailand. *Tourism Management*, 75, 550–568. https://doi.org/10.1016/J.TOURMAN.2019.06.020

Taff, B. D., Benfield, J., Miller, Z. D., D'antonio, A., & Schwartz, F. (2019). The role of tourism impacts on cultural ecosystem services. *Environments*, 6(4), 43. https://doi.org/10.3390/ENVIRONMENTS6040043

Tew, E. R., Simmons, B. I., & Sutherland, W. J. (2019). Quantifying cultural ecosystem services: Disentangling the effects of management from landscape features. *People and Nature*, 1(1), 70–86. https://doi.org/10.1002/PAN3.14/SUPPINFO

Torralba, M., Lovrić, M., Roux, J. L., Budniok, M. A., Mulier, A. S., Winkel, G., & Plieninger, T. (2020). Examining the relevance of cultural ecosystem services in forest management in Europe. *Ecology and Society*, 25(3). https://doi.org/10.5751/ES-11587-250302

Yarlagadda, M., Ettimalla, S., & Sri Davuluri, B. (2024). Zero-shot document classification using pretrained models. *Multifaceted Approaches for Data Acquisition, Processing & Communication*, 104–110. https://doi.org/10.1201/9781003470939-14

Yin, W., Hay, J., & Roth, D. (2019). Benchmarking zero-shot text classification: Datasets, evaluation and entailment approach. EMNLP-IJCNLP 2019 - *Conference on Empirical Methods in Natural Language Processing and 9th International Joint Conference on Natural Language Processing*, Proceedings of the Conference, 3914–3923. https://doi.org/10.18653/V1/D19-1404

Yin, W., Hay, J., & Roth, D. (2019). Benchmarking zero-shot text classification: Datasets, evaluation and entailment approach. *EMNLP-IJCNLP 2019 - Conference on Empirical Methods in Natural Language Processing and 9th International Joint Conference on Natural Language Processing, Proceedings of the Conference*, 3914–3923. https://doi.org/10.18653/V1/D19-1404

Zhao, Y., Han, Z., Zhang, C., Wang, Y., Zhong, J., & Gao, M. (2024). Coastal cultural ecosystem services: A bridge between the natural ecosystem and social ecosystem for sustainable development. Land, 13(9), 1352. https://doi.org/10.3390/LAND13091352

Paper #40

Title: A Methodological Framework for Lean Studentpreneurship: A Case Study of an AI-Driven Academic Support Platform

Author(s): Doğan Şengül, Ömer Faruk Işık, and Muhammed Küçükaslan (İstanbul Sabahattin Zaim University)

Abstract:
This paper introduces the concept of "Lean Studentpreneurship" and presents a structured framework for student-led innovation. Through a case study of an AI-powered academic support platform developed by two students, the authors demonstrate how lean startup principles, agile development, and experiential learning can converge in academic settings. The study offers actionable insights into how students can build market-ready solutions while remaining engaged in their studies.

Keywords: Lean Studentpreneurship, AI, Academic Innovation, Agile Learning, Educational Platforms

Paper #12

Title: Digital Transformation in Educational Applications: User Interface Design with Usability Tests

Author(s): Sevinc Gulsecen, Ecem Nur Yildizcan and Melike Kukut (Istanbul University)

Abstract:
This paper explores how adaptive, user-oriented interfaces enhance digital learning experiences. Within a theoretical framework centered on Education 5.0 technologies—AI, IoT, and VR—the authors analyze the usability of the Duolingo language app. Findings reveal that gamification boosts user engagement, while excessive notifications may hinder satisfaction. The study offers a roadmap for designing educational tools that personalize learning and improve usability.

Keywords: Education 5.0, Personalized Learning, Human-Computer Interaction, Adaptive Interfaces

Paper #64

Title: AI-Improved UAV Communication Networks for Remote and Disaster Regions: Enhancing Connectivity for Oman's Vision 2040

Author: Duygu Canbuldu and Aykut Hamit Turan

Abstract:
This study investigates the integration of artificial intelligence (AI) in UAV-based communication networks to enhance connectivity in remote and disaster-affected regions, aligning with Oman’s Vision 2040. It highlights how AI can improve routing, power management, and network efficiency. Simulation results demonstrate significant gains in signal quality, throughput, and energy optimization when compared to traditional UAV networks. The research supports the promise of AI-enabled UAVs in boosting digital inclusivity and green communication in geographically challenging areas.

Keywords: UAV Communication, Artificial Intelligence, Remote Connectivity, Energy Efficiency, Oman Vision 2040

Paper #18

Title: Blockchain-Driven Innovations in Aircraft Maintenance Operations: A Framework for Process Optimization

Author(s): Suheyl Belviranli (Istanbul Technical University) and Arafat Salih Aydıner (Istanbul Medeniyet University)

Abstract:
This paper explores how blockchain technology can optimize aircraft maintenance operations by enhancing trust, traceability, and efficiency. Leveraging features like immutability, transparency, and smart contracts, the study proposes a new framework based on Resource-Based View (RBV) Theory. The model was validated through workflow redesign and expert interviews, demonstrating potential gains in man-hours, error reduction, and competitive advantage.

Keywords: Aviation, Blockchain, Aircraft Maintenance, Smart Contracts, Process Optimization

Paper #30

Title: Role Ambiguity of Business Analysts: A Qualitative Investigation

Author(s): Said Altinişik and Mustafa Yanartaş

Abstract:
This study explores the role ambiguity of Business Analysts (BAs) in Turkey's private sector. Through interviews with professionals from diverse organizations, the paper reveals inconsistencies in the definition and scope of the BA role, often overlapping with system analysts, testers, or project managers. The findings highlight challenges such as unclear expectations, limited decision-making authority, and HR-related issues. The authors call for clearer role definitions and structured training to enhance project efficiency and BA career development.

Keywords: Business Analyst, Role Ambiguity, Agile, Project Management, Qualitative Study

Paper #48
Title: The Dark Side of Social Media: Doomscrolling and its Psychological Implications
Author(s): Faruk Dursun, Alpaslan Kibar and Ayça İrem Bayburtlu

Abstract:
This paper investigates the phenomenon of doomscrolling—compulsive consumption of negative news on social media—and its psychological consequences among university students. Drawing on survey data, the study reveals correlations between doomscrolling habits and symptoms of anxiety and depression. It highlights the urgent need for digital well-being strategies and proposes measures such as algorithmic filtering and digital literacy programs to mitigate harmful online behaviors.

Keywords: Doomscrolling, Social Media, Mental Health, Anxiety, Digital Well-being

Paper #30

Title: Role Ambiguity of Business Analysts: A Qualitative Investigation

Author(s): Said Altinişik and Mustafa Yanartaş

Abstract:
This study explores the role ambiguity of Business Analysts (BAs) in Turkey's private sector. Through interviews with professionals from diverse organizations, the paper reveals inconsistencies in the definition and scope of the BA role, often overlapping with system analysts, testers, or project managers. The findings highlight challenges such as unclear expectations, limited decision-making authority, and HR-related issues. The authors call for clearer role definitions and structured training to enhance project efficiency and BA career development.

Keywords: Business Analyst, Role Ambiguity, Agile, Project Management, Qualitative Study

Paper #48
Title: The Dark Side of Social Media: Doomscrolling and its Psychological Implications
Author(s): Faruk Dursun, Alpaslan Kibar and Ayça İrem Bayburtlu

Abstract:
This paper investigates the phenomenon of doomscrolling—compulsive consumption of negative news on social media—and its psychological consequences among university students. Drawing on survey data, the study reveals correlations between doomscrolling habits and symptoms of anxiety and depression. It highlights the urgent need for digital well-being strategies and proposes measures such as algorithmic filtering and digital literacy programs to mitigate harmful online behaviors.

Keywords: Doomscrolling, Social Media, Mental Health, Anxiety, Digital Well-being

Paper #47

Title: A SMART CITY MODEL FOR THE TÜRKİYE CONTEXT INTEGRATING DIGITAL TWINS AND ARTIFICIAL INTELLIGENCE

Author(s): Burak Arslan, Oğuzhan Arı &, Kübra Çalışkan

Abstract:
This study examines the digital technologies for smart city management and introduces a conceptual framework for a smart city management model tailored to Turkish public administration. The findings propose a model incorporating digital twins and artificial intelligence (AI) to enhance smart city governance. The proposed model is suitable for the Türkiye context. However, other countries can adopt similar models to address their unique urban priorities and problems. This study emphasizes the critical role of digital twins, AI, and automation in digitalization to address urban issues. Additionally, it presents a conceptual framework to enhance the effectiveness and efficiency of service and task forces in sustainable smart cities, aligning with Turkish public administration. This research provides essential insights for policymakers, urban administrators, planners, and researchers involved in smart city management.

Keywords: Smart City, Digital Twins, Artificial Intelligence, Automation, & Information Technologies

A SMART CITY MODEL FOR THE TÜRKİYE CONTEXT

INTEGRATING DIGITAL TWINS AND ARTIFICIAL INTELLIGENCE

Abstract

This study examines the digital technologies for smart city management and introduces a conceptual framework for a smart city management model tailored to Turkish public administration. The findings propose a model incorporating digital twins and artificial intelligence (AI) to enhance smart city governance. The proposed model is suitable for the Türkiye context. However, other countries can adopt similar models to address their unique urban priorities and problems. This study emphasises the critical role of digital twins, AI, and automation in digitalisation to tackle urban issues. Additionally, it presents a conceptual framework to enhance the effectiveness and efficiency of service and task forces in sustainable smart cities, aligning with Turkish public administration. This research provides essential insights for policymakers, urban administrators, planners, and researchers involved in smart city management.

Keywords: Smart City, Digital Twins, Artificial Intelligence, Automation, Information Technologies

1. INTRODUCTION

Sustainable cities leverage advanced technologies to strengthen the relationship between citizens and city governments, ensuring that all residents benefit from public services and have opportunities to co-create them (Golubchikov, 2020). In this context, a smart city represents a modern urban management and operations approach. The growing use of information technologies in cities has revitalized the smart city concept. Today, *smart* describes modern, intuitive, and intelligent urban environments (Wolniak et al., 2024).

Currently, there are no common frameworks for sustainable smart cities; only recommendations and methodological considerations are available. Smart city modelling should adopt a holistic and multidimensional approach (Dhingra & Chattopadhyay, 2016).

A smart, sustainable city aims to achieve key objectives—such as increasing quality of life, fostering economic growth, enhancing citizen well-being through accessible social and community services, and promoting environmentally sustainable development—in a way that is adaptable, reliable, scalable, accessible, and durable. Additionally, it guarantees the seamless delivery of vital public services and infrastructure, encompassing public transport, clean water, sewage and waste management, and telecommunications. A smart city must also be capable of addressing climate change and environmental challenges while implementing efficient regulatory frameworks and local administration to maintain equitable policies (Trindade et al., 2017).

Successful smart city projects require two essential competencies: first, understanding the impact of digital technologies within urban systems; and second, integrating solutions that overcome organizational resistance (Dembski et al., 2020). At the core of smart cities, the concept of digital twins, virtual representations of a city's natural environment, infrastructure, and operational systems, is found. Additionally, smart city institutions have digital twins, serving as virtual copies of physical assets, functions, and workflows.

A key driver of the business model of smart cities is the strategic use of technological advancements to address urban challenges effectively (Yang et al., 2024). This necessitates the combination of AI with data analytics and other disruptive technologies to optimise resource distribution, augment operational efficacy, and guarantee connectivity within metropolitan networks (Wolniak et al. 2024).

City brain is an AI-driven system that processes vast amounts of real-time data hosted by the city's and its institutions' digital twins to optimize decision-making. Urban AI has already manifested in applications such as autonomous vehicles, robotics, and city-wide intelligence networks, raising important considerations for the future of urban governance (Cugurullo, 2020).

As AI becomes increasingly integrated into smart infrastructure and big data analysis, cities will become even smarter. Key benefits include improved safety, sustainability, quality of life, and overall citizen experience. However, AI also introduces challenges, particularly regarding data privacy and critical infrastructure security, which governments and public institutions must actively manage. Over the next five years, AI—particularly generative AI—is expected to play a transformative role in digital government services, smart transportation, and interactive digital twins (Roth & Incera, 2024).

AI enhances urban management by simulating different scenarios, anticipating potential challenges, and supporting data-driven decision-making. It facilitates strategic planning and resource optimization while offering insights into how changes in urban structure and institutional functions may impact operations. AI also enables the coordination of tasks to maximize efficiency and sustainability, directly integrating operational directives into automation technologies. Automation, in turn, enhances service delivery by increasing speed, accuracy, productivity, and quality while minimizing human error. The smart city model strengthens planned urban management and improves crisis response through real-time, observation-based feedback.

Smart cities are geographic areas where high-tech solutions span information technologies, logistics, and energy production—are integrated to enhance citizen well-being, social participation, and environmental sustainability (Bernyukevich, 2023). Implementing a smart city model with these capabilities would significantly enhance urban administration's efficiency, cost-effectiveness, and quality, benefiting citizens' welfare and guaranteeing the sustainable use of resources. Hence, this study proposed a smart city model for smart cities based on a comprehensive literature review, along with observations and analyses derived from professional experience and municipal smart city initiatives. The findings are discussed in two sections:

- *The Role of Information Technologies in Smart Cities* – This section examines how information technologies contribute to smart city management and analyzes some case studies. It also presents a model outlining the role of digital technologies within the hierarchical structure of smart city governance.

- *Smart City Implementation within Turkish Public Administration* – This section proposes a model for integrating smart city principles into Türkiye's public administration framework.

While various smart city models exist (Wolniak et al., 2024), many—including those in ongoing smart city initiatives in Türkiye—have overlooked critical aspects. Specifically, they have failed to emphasize the need for digital twins, neglected centralized city management in the context of modern governance principles, and largely ignored the integration of rapidly evolving automation and robotics technologies into urban systems.

The primary aim of this study is to underscore the importance of digital twins in smart city initiatives, advocate for AI-driven centralized management, and highlight the role of automation in improving efficiency and cost-effectiveness. The study analyzes how these key technologies function within smart cities and provides a structured approach to their integration. Accordingly, the research questions of this study are as follows:

- What are the essential digital technologies for a smart city, and what roles do they play?
- How can a Smart City Model be designed as an open system based on the relevant digital technologies?
- How can this model be effectively implemented within Turkish public administration?

2. LITERATURE REVIEW

Information Technologies for Smart Cities

Smart cities leverage advanced technologies, comprising artificial intelligence, blockchain, big data analytics, the Internet of Things, 5G networks, unmanned aerial vehicles (UAVs), smart sensors, and imaging technologies. These innovations form the foundation of smart systems and grids across various functional domains, such as smart infrastructure, transportation, healthcare, energy, governance, and administration (Karri et al., 2024; Wolniak et al., 2024). A truly smart city emerges through the seamless integration of these technologies.

However, a smart city is more than just a collection of advanced systems—it is an interconnected network of digital twins replicating various aspects of the city's operations and development. The concept of a *digital twin city* constitutes a remarkable development in designing and managing smart urban environments (Ivanov et al., 2020).

High-level design and strategic planning tailored to each city's unique characteristics are essential for full smart city functionality. Establishing a smart city operations center—often referred to as an *operation brain*—is crucial for overseeing and optimizing urban functions (Deren et al. 2021).

Automation technology is also becoming increasingly integrated into daily life and industrial production, with electricity as the foundation of modern science and technology. Today, electrical and automation technologies have reached an advanced stage, driving progress across numerous high-tech industries. In the future, electrical engineering and automation will continue to play a vital role in ensuring smart cities' efficiency, safety, reliability, and sustainability. These innovations will enhance urban life, making cities more convenient, comfortable, and environmentally friendly (Chen 2024).

Digital twins are indispensable for seamlessly integrating advanced technologies in smart cities. AI is equally critical, enabling centralized management of smart systems and grids. Meanwhile, automation plays a fundamental role in executing and controlling smart sensing, planning, command, and feedback processes. Together, digital twins, AI, and automation form the core technological pillars of scientific and efficient smart city management.

Urban Digital Twins

Urban digital twins are replicas of a city's physical infrastructure and functional systems. They provide a real-time, continuously updated view of the urban environment by collecting data from sensors, mobile devices, and the IoT (PwC, 2022). As complex data models, urban digital twins facilitate collaborative planning and decision-making processes (Dembski et al., 2020). They represent not only a city's infrastructure and superstructure but also all the tasks performed and services delivered within it.

The primary goal of urban digital twins is to enhance the efficiency of city planning, construction, disaster response, energy management, communication, logistics, transportation, and overall urban sustainability (Deng et al., 2021). By assessing the real-time status of environmental systems, they enable optimal solutions and contribute significantly to ecological sustainability (Shahat et al., 2021).

For example, a digital replica of a city’s physical landscape can be constructed using local geographic data. This allows urban planners to analyze and predict the impact of proposed developments on air quality, mobility, water management, and building emissions with high accuracy (Yıkıcı, 2023). As a data-driven planning tool, digital twin projects provide a 3D model of the city, supporting scenario development and real-time project execution based on up-to-date information (Republic of Türkiye Istanbul Metropolitan Municipality Information Technology Department Smart City Branch Directorate, 2021).

While many smart city initiatives focus on embedding digital technologies into urban infrastructure, some perspectives emphasize the broader impact of smart cities. These perspectives suggest that smart cities improve public services and environmental quality and enhance local economic competitiveness through innovation. Additionally, they argue that smart city development should not be limited to government-led initiatives but should emerge from the collective actions of individuals and private entities leveraging smart services (José & Rodrigues, 2024).

The Istanbul Metropolitan Municipality (IMM) has adopted a strategic approach to real-time urban monitoring through a comprehensive 3D city model. This model integrates data from geographic information systems, high-resolution aerial photography, satellite imagery, and street-level panoramic images to enable proactive urban management (Republic of Türkiye Istanbul Metropolitan Municipality Information Technology Department Smart City Branch Directorate, 2021). In summary, urban digital twins play an important role in building smart, efficient city management systems. By providing a dynamic 3D virtual environment, they support urban planning, enable automation-driven decision-making, facilitate collaboration, monitor execution, assess operational outcomes, and enhance feedback mechanisms.

Digital Twin Institutions

The development of digital twins as part of urban digital twin initiatives will drive smart planning, foster significant innovations in management and services, and serve as a foundational step toward building smart cities (Deren et al., 2021). The concept of digital twins should focus on digitizing the service environment, service providers, service development processes, and service delivery mechanisms (Kumaş & Erol, 2021).

Digital twin technologies serve as critical solutions for institutions that provide services and contribute to urban infrastructure.

With the emergence of Industry 4.0 technologies, digital twin technology has made significant strides, offering substantial benefits to businesses and institutions. Its potential advantages have significantly increased its appeal. Research indicates that the market size for digital twin technology is currently valued at approximately \$3.1 billion, with a predicted increase of \$48.2 billion by 2026 (Leng et al. 2021).

Additionally, it is estimated that 30% of Global 2000 companies will leverage data from digital twins of products and assets to enhance product innovation and corporate efficiency, resulting in a 25% increase in operational efficiency (Bulut, n.d.).

The application of digital twins varies across industries. For instance, in the energy sector, digital twins are primarily utilized for monitoring and analytical evaluation to optimize service delivery. In the transportation sector, they serve as tools for capacity planning, transportation network optimization, and real-time monitoring of transportation assets in train stations and airports (Handan, 2021).

Ultimately, integrating institutional digital twins plays a crucial role in developing and managing smart cities. This process involves creating virtual representations of institutional duties and responsibilities, physical assets, business processes, and service offerings in a digital environment. Cities can develop and sustain a comprehensive digital twin ecosystem by establishing digital twins of institutions. This initiative represents a key policy objective, enabling institutions to harness the power of digital technology to pursue more sustainable, efficient, and inclusive smart cities that benefit both citizens and stakeholders.

Artificial Intelligence

AI to function effectively in a smart city, it must have the ability to learn from its surroundings, extract meaningful insights from collected data, handle incomplete information and uncertainty, determine the best course of action, and make autonomous decisions—potentially surpassing human capabilities in these areas. In this context, AI in smart cities is currently represented by autonomous vehicles, robotics, and the concept of the "city brain" (Cugurullo, 2020).

AI is a pivotal technology that integrates essential aspects of smart cities, encompassing urban life, government, economy, environment, and public services. AI and other advanced technologies have become powerful tools for developing optimal policies to address complex urban challenges, encompassing intelligent transportation networks, privacy and security issues, efficient energy grids, and advanced medical technologies (Szpilko et al. 2023).

The fast development of AI has significant opportunities to tackle urban challenges and increase the welfare of citizens. Key applications of AI in smart cities include smart mobility, environmental management, governance, economic development, and citizen engagement (Wolniak & Stecuła, 2024).

Moreover, AI's integration with big data analytics is proving to be a game-changer for smart cities. Utilising AI-driven data analysis, municipalities can optimise resource distribution, improve infrastructure management, and provide innovative services that respond to changing requirements (dos Santos et al., 2024).

In summary, Artificial intelligence is set to transform urban administration by analysing extensive datasets derived from sensors and social media. AI can optimize urban planning and automate task assignments through machine learning algorithms and real-time feedback. As the "brain" of the smart city, AI is the most critical component, driving efficiency, safety, and sustainability.

Automation

Automation in smart cities refers to using advanced technologies to perform tasks with minimal human intervention. This includes AI, 5G connectivity, big data analytics, the IoT, and augmented/virtual reality technologies, all of which help streamline processes and enhance productivity (Zara, 2023). By leveraging automation, cities can respond more effectively to real-time data transmitted by IoT-connected devices.

For example, automated street lighting systems use sensors to detect light and motion, ensuring that streetlights turn on only when needed and switch off during inactivity. This promotes energy efficiency and enhances urban operations' sustainability (Gomstyn & Jonker, 2023).

The global shift toward AI and automation in urban environments continues to gain momentum. Many cities in Australia and Canada are adopting AI and robotics into their infrastructure, while Moscow has also made significant advancements in this area (Golubchikov & Thornbush, 2020).

The automation in transportation alone can yield numerous benefits, including alleviating traffic congestion and reducing emissions and energy consumption, minimizing accidents and material damages, and optimizing the use of parking spaces (Lohmann & Van der Zwaan, n.d.). Ultimately, automation plays a critical role in increasing productivity, efficiency, and cost-effectiveness within smart cities. Even outside the scope of smart city initiatives, automation is already deeply integrated into urban life and will continue expanding into a growing number of services.

Integrating digital twins, AI, and automation represents a significant step toward building truly smart cities. Digital twins, which provide historical and real-time data on urban infrastructure, services, and activities, are foundational for implementing AI and automation in city management.

AI systems powered by high-capacity computing can leverage digital twins of institutions as edge computing nodes, processing vast amounts of data collected from local data centers, IoT devices, and sensors throughout the city. By continuously monitoring this data, AI can predict issues, optimize operations, and enhance decision-making processes.

Machine learning algorithms enable AI to make data-driven urban planning and management decisions. AI systems can generate task orders autonomously or with human oversight and distribute them to relevant entities. In critical situations, such as major disasters, AI can be authorized to take direct action, automating governance for rapid response and crisis management.

Automation, closely linked with AI and digital twins, streamlines routine tasks by continuously monitoring and controlling urban assets. Highly standardized processes like smart public transportation systems can be fully automated using edge computing and robotic technologies. Even complex functions like maintenance, security, and resource allocation can be automated based on real-time feedback, improving efficiency and adaptability.

Furthermore, adaptive and self-learning systems can enhance the city's responsiveness by adjusting their parameters in real-time based on evolving conditions. This synergy between digital twins, AI, and automation strengthens operational efficiency, optimizes resource utilization, and fosters the development of sustainable and resilient urban environments.

Table 1 below illustrates the physical structures and information technologies in smart cities.

Table 1: Physical Structures & Information Technologies in Smart Cities

Smart City Components	**Physical Structures, Information Technologies and Applications**
Digital Twin City	• Geographic features, including geology and climate • City infrastructure (e.g., roads, bridges) and superstructures (e.g., buildings, parks, gardens) • Utility networks (e.g., water, sewage, electricity, natural gas, fiber-optic communication systems) • IoT devices, cameras, and other sensors • Transportation, security, disaster response systems
Digital Twins of Institutions	• Physical assets of institutions • Roles and responsibilities, including regulatory information • Internal policies and business processes • Local data centers
Artificial Intelligence	• Machine learning and deep learning algorithms • Data analytics programs utilizing big data
Automation	• Automated governance processes • Edge computing technologies • Robotics applications

Smart City Management

The efficacy of smart city initiatives is driven by key factors such as management and organization, technology, administration, public context, economy, and information systems infrastructure (Khan & Zia, 2021). Among these, the technology infrastructure—comprising information and communication systems—plays a critical role in maintaining accessibility, integration, and quality of services. The core of this technological infrastructure is the digital twin city, which possesses four fundamental characteristics (Deren et al., 2021).

- Accurate Mapping – Provides a precise virtual representation of urban infrastructure.
- Virtual-Real Interaction – Ensures real-time synchronization between the digital and physical worlds.
- Software Description – Defines urban structures and operations in digital formats for analysis.
- Smart Feedback – Enables AI-driven learning and optimization for continuous urban improvements (Deren et al., 2021)

By integrating digital twins and AI and providing automation, smart cities can optimize urban management, improve resource allocation, and enhance sustainability. The fusion of these technologies represents a shift toward a fully digitized, data-driven, and self-optimizing urban ecosystem. The Table 2 below illustrates the key roles and functions of smart city components representing the smart city technologies and their applications

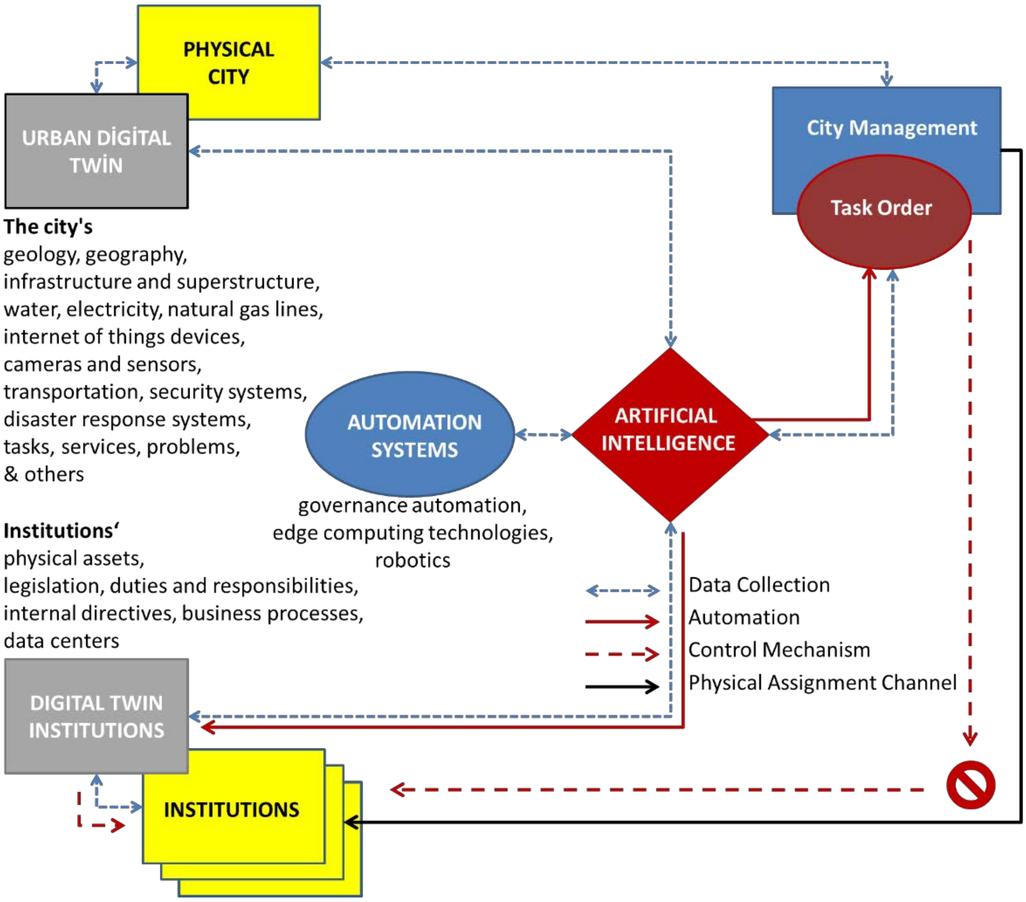
Table 2. Smart City Components, Key Roles and Functions

Smart City Components	Key Roles & Functions
Digital Twin City	• Creates a real-time and historical virtual representation of the city • Collects and integrates data from urban infrastructure, IoT devices, and sensors • Supports scenario-based planning, simulations, and predictive analytics • Enhances coordination between city departments and services

Digital Twins of Institutions	• Digitally represents an institution's physical assets, services, and processes • Enables seamless integration with the digital twin-city • Facilitates data-driven decision-making for optimized operations • Supports automation in monitoring, planning, and service delivery
Artificial Intelligence	• Processes and analyzes big data for insights and optimization • Supports predictive maintenance, demand forecasting, and emergency response • Enhances decision-making with machine learning algorithms • Automates governance and public services with real-time monitoring and control
Automation	• Reduces human intervention in routine processes • Enables smart transportation, adaptive traffic management, and smart energy grids • Supports autonomous public services, such as automated waste management and security • Enhances operational efficiency and sustainability through automated systems

Considering ideas and concepts introduced in Table 1 and Table 2, Figure 1 presents a schematic representation of the functions performed by smart city components, along with the relevant entities and data flow between them.

Figure – 1 Smart City Model and Management



In this model, AI serves as the brain of the smart city, with digital twins and data centers acting as the primary sources of information. While edge computing technologies—functioning like nerve endings—can resolve issues locally, they still transmit the full dataset to AI. AI processes data from digital twins, edge computing, and robotic applications. Governance automation then distributes electronic task orders to the relevant points. The city administration determines which tasks can be executed without additional human oversight, while tasks requiring supervision, along with their assignments and orders, are subject to approval by authorized personnel.

3. METHODOLOGY

This study employed a literature review as its primary research method. The review focused on the advantages, limitations, and advanced applications of digital twins, artificial intelligence, and automation within the context of smart cities. The analysis began with summarizing and categorizing key findings, themes, and gaps using qualitative analysis techniques such as thematic analysis and content analysis (Dehkordi et al., 2021). Additionally, observations, document reviews, professional experiences, and insights gained from the researchers' involvement in smart city projects were incorporated into the qualitative analysis.

Three research questions guided this study:

Identification of Key Information Technologies for Smart Cities

The first research question was explored through literature analysis. The review focused on identifying and synthesizing the essential information technologies used in smart cities and their critical roles in ensuring effective, economical, and efficient smart city management. Academic studies in this field were systematically examined.

Analysis of Information Processing Models of Smart Cities

The second research question aimed to provide a comprehensive overview of various information processing models conceptualized and implemented in smart city contexts in Türkiye and globally. This study identified existing models and discussions in the literature by examining the theoretical foundations, conceptual frameworks, and empirical evidence related to smart city management information processing models. A comparative analysis was conducted, focusing on real-world applications in Istanbul and Balıkesir (Türkiye) and London (United Kingdom). The study investigated the contextual factors, stakeholder dynamics, and implementation strategies influencing the adoption and deployment of these models in smart city projects.

Development of a Smart City Model for Türkiye

The third research question was addressed through a combination of literature analysis, case studies, and comparative evaluations. The study aimed to provide insights into the theoretical advantages and potential benefits of a smart city information management model tailored to public administration conditions in Türkiye. Expected outcomes, anticipated impacts, and perceived benefits of implementing a specific management model for smart cities in Türkiye were analyzed and discussed.

4. FINDINGS

Smart City Examples: Implementations of London, İstanbul, and Balıkesir

These cases explore the role of information technologies and systems in the smart city transformation of London, İstanbul, and Balıkesir, highlighting their goals and current applications in the journey toward becoming smart cities.

London

In London, a more collaborative approach is being embraced to leverage big data and smart technology in addressing both current and future challenges. Efforts are underway to mobilize the resources of government services, premier universities, and the technology sector. To guide this initiative, London has appointed its first Chief Digital Officer and established a new Smart London Board of Directors, alongside a roadmap to ensure the effective use of big data and digital technologies (Greater London Authority, 2018).

According to the roadmap, the strategy for London focuses on producing more user-designed services, launching the London Data Analytics Office program, developing a cybersecurity strategy, supporting an open ecosystem to foster innovation, planning 5G projects, expanding fiber infrastructure, enhancing WiFi networks, building next-generation smart infrastructure, promoting standards for smart technologies, increasing big digital data, and developing the computing skills and digital talent of both the workforce and citizens. Additionally, the strategy emphasizes integrating collaboration among all subsystems in London first and later collaborating with global cities (Greater London Authority, 2018).

The completion of all digital maps of England by the Ordnance Survey in 1995 (ESRI) gave London a significant advantage in terms of geographical data for its smart city journey. A recent study revealed that London was selected as the city best prepared for a smart future in Europe, earning an overall score of 73.7 out of 100 (Proptechos, n.d.). The London Data Center plays a key role in the smart city strategy, with Londoners enjoying free access to information and statistics about the city. Smart city technologies have become integral to daily life in London, with vast amounts of real-time data provided through 5G networks, a broad network of sensors, cameras, drones, robotics, and automation, all contributing to the safe management of the city (Puttkamer, 2023).

For smart city management in London, the city has advanced its digital twin, big data management, AI-driven data processing, robotics, and automation. As the work progresses, the collaboration between all subsystems has been identified as a crucial goal in creating a unified management system.

Istanbul

The implementation of the smart city governance model in Istanbul is addressed through four transformation stages: smart city management, smart decision-making, smart collaboration, and smart management. The first stage focuses on the effective and efficient implementation of the right policies without requiring changes to the existing management structure and processes. The second stage emphasizes the restructuring of decision-making mechanisms, while the third and fourth stages introduce smart management and collaboration as essential components of the transformation (Republic of Türkiye Istanbul Metropolitan Municipality Information Technology Department Smart City Branch Directorate, 2021).

Innovative technologies improve managerial rationality by utilising more accessible and precise data for decision-making and execution. Smart management embodies a novel paradigm of electronic governance that employs modern technology to link and unify information, processes, institutions, and physical infrastructure. As part of the first-stage initiatives, several bodies were established, including the Smart City Governance Platform and Coordinator, Smart City Executive Board, Smart City Advisory Council, and the Smart City Thematic Area Project Coordination Units. Additionally, the Smart City Implementation Office was set up to oversee the execution of these efforts (Republic of Türkiye Istanbul Metropolitan Municipality Information Technology Department Smart City Branch Directorate, 2021).

Studies have been launched to create a management information system for Istanbul's smart city governance to analyze data gathered from the city, create a digital twin of the city, and conduct scenario analyses based on this data.

Balikesir

In Balıkesir, the smart city journey began with adopting Geographic Information Systems solutions. A roadmap associated with GIS was developed as part of the municipality's duties and responsibilities. This led to the creation of Türkiye's first Geographic Data Regulation, which aligns with national legislation and data standards. The regulation aims to establish standard applications and define the roles and responsibilities of relevant units to manage geographic information effectively, economically, and efficiently, enabling the city to make accurate, spatially-based decisions (Balikesir Metropolitan Municipality, 2023).

In efforts to develop the smart city's management information systems, the Data Management Center was established to manage big data, with a particular focus on geographic data. Initiatives such as disaster management and the application of AI and machine learning to big data have also been launched. Around 600 out of an anticipated 3.000 data layers for the city's digital twin have been made available to the data center, with updates provided every month when not available online. The digital twin project is nearing completion for the Metropolitan Municipality (Balikesir Metropolitan Municipality, 2024).

As part of the city's real-time data-based urban management, particular attention is being paid to automation, leveraging IoT devices, vehicle sensors, smart cameras, and especially traffic management systems (Smart cities portal, n.d.).

All of these initiatives aim to enhance city management, make public services more effective and evidence-based, and enable sustainable planning and management from a unified platform. The smart city management information system will seek to make city governance more effective, sustainable, efficient, and cost-effective, addressing complex, multifaceted problems with a holistic approach (Balikesir Metropolitan Municipality, 2024).

Cities are considered smart when management can optimise the utilisation of both tangible and intangible assets, enhance inhabitants' quality of life, improve resource productivity, and address new challenges. The literature on smart cities is divided into two sub-sections. Some researchers present studies on smart cities by paying attention to the dimensions and areas of smart cities. In contrast, the other group of researchers focuses on using cross-functional organizations to perform smart city initiatives and the role and characteristics of public administrators (Michelucci et al., 2016).

The tangible assets discussed in this study are the physical city, the management structure of this city, the institutions serving the city and their physical assets, and especially information and automation technologies.

A smart city is a transformation project. The driving forces of institutional transformation achieve transformation by providing organizational and operational maturity. As strategy, market and sales, services and products, organizational design, resources, and stakeholder participation develop, organizational and operational maturity also develops (Bahner & Stroh, 2004).

Accordingly, it may be necessary to express the strategic level duties of smart city management as follows.

- Preparation of the smart city transformation strategy document (strategic plan) and obtaining the approval of all stakeholders,

- Establishing a smart city management organization in accordance with the legislation and allocating resources,
- Determination of the basic purpose and operational goals, the services and tasks to be performed, and service and task performance standards.

In the smart city management model, authorized operation and service production levels that can fulfil management functions at all levels should be established, and standardized tasks should be determined.

5. PROPOSED CONCEPTUAL FRAMEWORK

City Management Responsibility in Türkiye

This section attempts to create a model proposal on how institutions responsible for the management of cities in Türkiye can take part and play a role in smart city management.

In Türkiye, although Governors are responsible for the general administration of the province, communication between Ministries and Provincial organizations and monitoring of work, and ensuring coordination of Provincial services and duties between Municipalities and Ministry organizations (The Provincial Administration Law No. 5442/ Article 9 and 21); the management responsibility for services and duties in the city is given to Municipalities. Municipalities are responsible for a wide range of duties and services, from zoning plans to business licenses, highway and waterway transportation, urban transportation planning and construction of roads, use of water, disposal and reuse of wastewater, solid waste, environmental protection and control, surveillance of public health, safety of food supply, social facilities, social affairs and social services, support and execution of arts, sports, widespread education and cultural activities, development of agriculture, tourism, industry and trade in the city, and taking precautions and intervention against disasters when necessary. Decisions are the duties of the Municipal Councils, and execution is the duty of the Mayors. In addition, the Municipalities are responsible for digitalising the city, developing a strategic vision and strategic plan for smart city initiatives (Metropolitan Municipalities Law No. 5216/Article 7 and Municipalities Law No. 5393 /Article 18).

The 1/100,000 scale Environmental Regulation Plans published by the Ministry of Environment, Urbanization and Climate Change dictate the decisions of the Central Government regarding settlement and land use, including residential areas, industrial zones, agriculture, tourism, and transportation. Municipalities also coordinate their significant investments in the city with the Central Government through the Ministry of Environment, Urbanization and Climate Change (2018/30474 Decree Law). The tasks addressed by the Central Government under the title of disaster-resistant living spaces and sustainable environment in the 5-Year Development Plans determine targets within the scope of disaster management, urban transformation, urbanization, housing, environmental protection, urban infrastructure, regional development, rural development subheadings (Türkiye's Twelfth Development Plan 2024-2028), and these targets directly bind the Municipalities responsible for the management and execution of duties and services in the city.

According to the legislation in force in Türkiye, it is considered appropriate for the smart city upper management duties to be carried out by the Metropolitan or Provincial Municipalities in coordination with the Central Government and the Governor, the operations-level duties to be carried out by District Municipalities, Governorship Directorates, District Governorships, Metropolitan Municipality units and other equivalent institutions and organizations, and the lower-level duties and services to be carried out by the subunits of these institutions.

Therefore, it is a necessity to create digital twins of all institutions serving the city with their subunits and all physical assets. Data management centers that will provide data communication with AI for these units whose digital twins will be created should also be established.

A Smart City Model for Türkiye

The advantages of implementing a specific smart city model change based on the context and goals of each city.

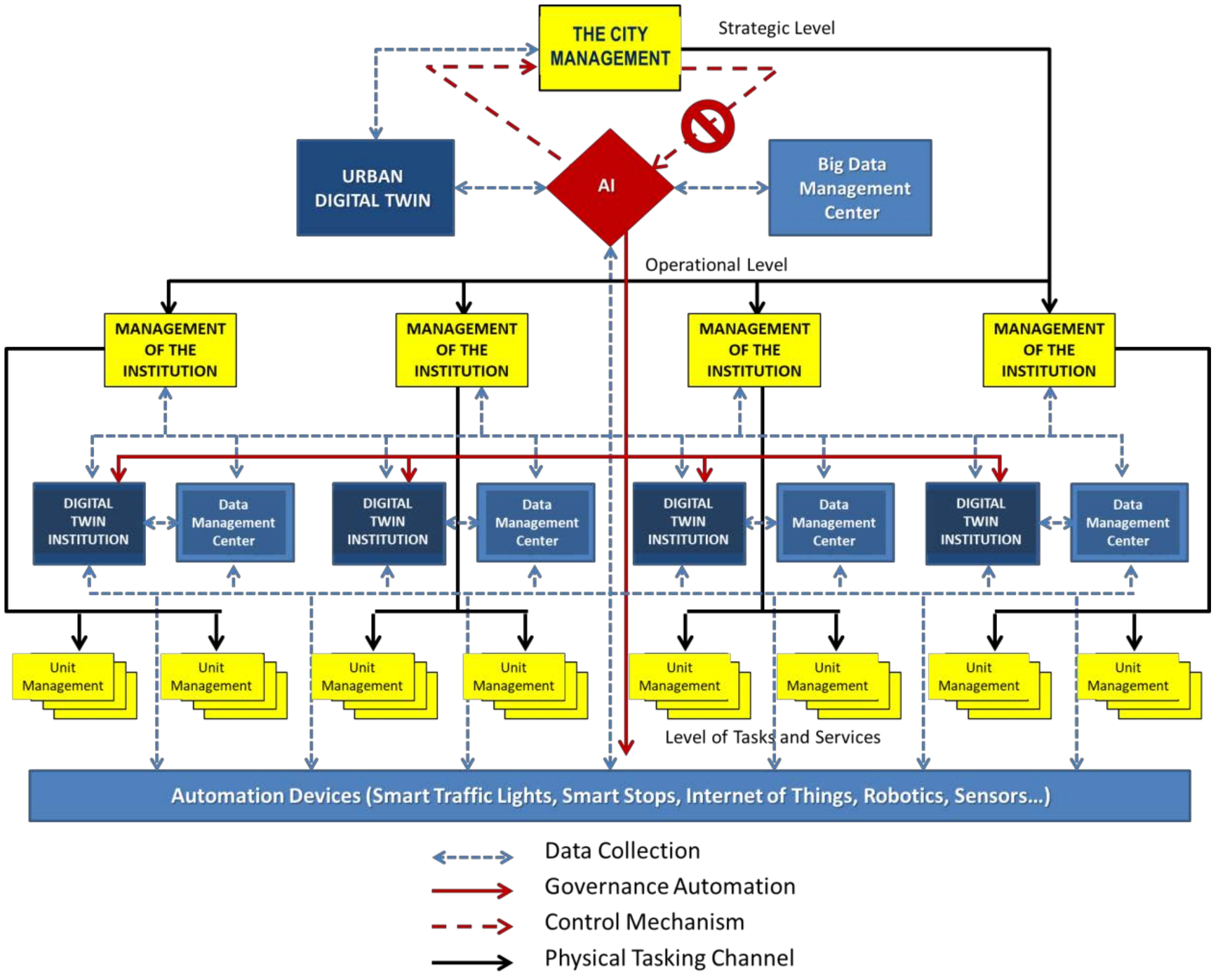
The strategic goal determined at the highest level on the path to smart cities in Türkiye is to implement Smart Cities, ensure their effectiveness and sustainability with the support of the cooperation of ecosystem stakeholders and holistic, planned and encouraging financial management system within the framework of national and local governance mechanisms, appropriate organizations, institutional architecture and legislation to which all stakeholders will contribute, and the cooperation of ecosystem stakeholders (Türkiye's Ministry of Environment, Urbanization and Climate Change 2020-2023 National Smart Cities Strategy and Action Plan).

The field of Smart Cities in Türkiye has been addressed with distributed legislation within the scope of a multi-stakeholder ecosystem and a multi-layered governance model. In this context, there is a need to foster a unified national strategic viewpoint across stakeholders supported by legislation in the field of Smart City. The common strategic perspective to be provided will ensure the coordination of Smart City studies and the sustainability of the Smart City Governance Mechanism and stakeholder organizations involved in this mechanism, which are necessary to implement policies in this field (Türkiye's Ministry of Environment, Urbanization and Climate Change 2020-2023 National Smart Cities Strategy and Action Plan).

The smart city governance mechanism is expected to be implemented with the help of information systems. In Türkiye, the city and its tasks and services can be managed centrally by the metropolitan or provincial municipalities at the strategic level. The tasks and services can be carried out effectively by institutions at the operational level and by the units of the institutions at the lower level. Advanced technologies and systems are used to make each level smart. Those technologies minimise human inadequacies with correct prioritization in the services and tasks carried out in the city and increase the speed of intervention, efficiency, productivity, accuracy and quality. With this understanding, the smart city model proposed in this study is an open system.

For the proposed model, there is a need for a competent AI established by the Metropolitan or Provincial Municipalities, digital twins and data management centers of the institutions producing services in that city, and a widespread automation structure at lower levels. A comprehensive smart city model is presented in Figure 2.

Figure 2 – A Smart City Model for Türkiye



This model provides data flow automatically at every level, and data management is performed at every level. AI, which is kept under strategic control by the upper management, optimizes planning and coordination, and cooperation efforts and can directly communicate the most appropriate course of action to the relevant parties. The city administration should control works subject to specific protocols. At every level and stage, feedback is provided between the city's digital twin and digital twin institutions and data centers, and current data is updated. Previous data is archived within data automation. Plans for routine and non-controlled jobs and assignments within this framework can be directly communicated to their responsible persons or robots as task orders.

Edge computing capabilities enable management functions (analysis, planning, ordering, control and evaluation) to be resolved at different city service levels (operations, task and service production or smart device levels). The management of some data sets in lower-level data centers, and the dissemination of such capabilities can lighten the burden of AI, which is the brain of the city.

Information systems are high-cost technologies. For example, backing up valuable current big data at geographically distant points can lead to additional costs. However, the smart city journey has no obstacle other than cost. Smart city formation is a goal that can be achieved by management information systems experts who will work patiently and devotedly for this purpose and who know their subject and technology well.

6. CONCLUSION

This study tries to shed light on the implementation of management information systems in smart cities and the approach to their implementation in Turkish Public Administration through a literature review and case studies.

According to the literature review, a smart city management information system created by combining digital twins, AI, and automation with many modern technologies will support smart cities in preparing for the future once it is established and operated. In addition, a model is proposed in this study on how digital twins, AI, and automation technologies can be used as the infrastructure of a smart city.

The answers to the determined research questions are clearly stated. The management information technologies that should be used primarily in a Smart City and the roles of these technologies in a smart city are explained. According to the determined division of labour, a 'Smart City Model' is presented as an open system. Accordingly, application examples in London, Istanbul and Balıkesir provinces are examined.

According to the evaluations, London has made quite good progress in the smart city journey, and cities in Türkiye, especially İstanbul and Balıkesir, continue their smart city journeys within the framework of their special conditions. In particular, the use of smart city technologies in each city and the rate of benefiting from these technologies vary according to local conditions. London is at an advanced level in issues such as digital twins, big data, and robotic automation, and Istanbul is trying to develop its work in this regard through various boards. Balıkesir, on the other hand, has prioritised the management of big data, especially geographic information systems, and has achieved partial success in AI technology, robotics and automation. The conceptual framework for implementing smart city information systems in the Turkish Public Administration has been presented in the final part of the study.

The originality of this study lies in its comprehensive analysis of how digital twins, AI, and automation can be used in smart city management. While numerous academic studies examine smart applications in cities, this study stands out by performing an analysis of how all these applications can be managed from a single source, how efforts can be combined and how efficiency, economy and high productivity can be achieved. It provides a detailed understanding of the various strategies used in the smart city field by examining the various approaches adopted in London, Istanbul and Balıkesir to promote sustainable urban development and improve citizens' quality of life.

Limitations of the Study

One of the main limitations of this article is that the evaluations were conducted for only three cities. In addition, the literature and secondary data are used for the cases of London and Istanbul. Balıkesir province was analyzed more thoroughly through observation, document review, experience and participation in existing workshops. Although these cities offer significant insights into the implementation of information technologies and systems in the development of smart cities, they constitute just a fraction of the global and national environment in Türkiye. The omission of an analysis of cities from diverse locations with varying socioeconomic conditions and cultural settings may restrict the generalisability of the results.

Future Research

Future research on smart cities could explore the long-term impacts of business strategies on sustainability, economic advancement, and social engagement, as well as integrating emerging technologies like digital twins, artificial intelligence, robotics, and automation into existing infrastructure.

Theoretical Contribution

This study presents a smart city information management model suitable for Turkish Public Administration as a conceptual framework. This framework enhances our theoretical comprehension and establishes a benchmark for further research endeavours in this domain. Furthermore, the study substantiates the theoretical framework of Turkish Public Administration legislation about governance within the context of smart cities and offers an enhanced framework. It can contribute to the experimental demonstration of the effectiveness of the proposed structure in real-world environments and to the further development and improvement of current practices.

Managerial Contribution

From a managerial perspective, the study provides a feasible model for urban policymakers, urban planners, and public sector managers involved in smart city initiatives and an evidence-based strategy proposal for urban governance. City managers can use these insights to establish assessment frameworks that guarantee the implementation of identified projects, efficient use of resources and achievement of predefined goals. The results presented by this study can create environments conducive to sustainable economic developments that encourage technological advancement and innovation in smart cities.

REFERENCES

Bahner, R. R., & Stroh, L. K. (2004). The Transformation Management Model: A Total Evaluation Route to Business Change Success. *Problems and Perspectives in Management*, *2*(4), 180–191.

Balıkesir Metropolitan Municipality (2024, 6 November). *Smart City Management era in Balıkesir* on February 15, 2024 https://balikesir.bel.tr/haberler/balikesirde-akilli-sehir-yonetimi-donemi

Balikesir Metropolitan Municipality (2023, 24 October). *Balikesir metropolitan municipality geographical data regulation.* https://balikesir.bel.tr/mevzuat accessed on 28 November 2024

Bernyukevich, T. (2023, January) *Risks of smart city projects: definition, typology, management* [AIP Conference Proceedings] Construction the formation of living environment: form-2022, Moscow, Russian Federation https://pubs.aip.org/aip/acp/article-abstract/2791/1/050043/2905427/Risks-of-smart-city-projects-Definition-typology?redirectedFrom=fulltext

Bulut, T. (n.d.) Can a digital twin of a human be created? Tevfikbulut.com

https://tevfikbulutcom.wordpress.com/wp-content/uploads/2020/07/c4b0nsanc4b1n-dijital-c4b0kizi-oluc59fturulabilir-mi-1.pdf

Chen, J. (2024). Application of Electrical Automation in Smart City. *Academic Journal of Science and Technology*, *12*(2), 2771–3032.

Cugurullo, F. (2020). Urban Artificial Intelligence: From Automation to Autonomy in the Smart City. *Frontiers in Sustainable Cities*, *2*. https://doi.org/10.3389/frsc.2020.00038

Dehkordi, A. H., Mazaheri, E., Ibrahim, H. A., Dalvand, S., & Gheshlagh, R. G. (2021). How to Write a Systematic Review: A Narrative Review. In *International Journal of Preventive Medicine* (Vol. 12, Issue 3, pp. 12–27). Wolters Kluwer Medknow Publications. https://doi.org/10.4103/ijpvm.IJPVM_60_20

Dembski, F., Wössner, U., Letzgus, M., Ruddat, M., & Yamu, C. (2020). Urban digital twins for smart cities and citizens: The case study of herrenberg, germany. *Sustainability (Switzerland)*, *12*(6). https://doi.org/10.3390/su12062307

Deng, T., Zhang, K., & Shen, Z. J. (Max). (2021). A systematic review of a digital twin city: A new pattern of urban governance toward smart cities. *Journal of Management Science and Engineering*, *6*(2), 125–134. https://doi.org/10.1016/J.JMSE.2021.03.003

Deren, L., Wenbo, Y., & Zhenfeng, S. (2021). Smart city based on digital twins. *Computational Urban Science*, *1*(1). https://doi.org/10.1007/s43762-021-00005-y

Dhingra, M., & Chattopadhyay, S. (2016). Advancing smartness of traditional settlements-case analysis of Indian and Arab old cities. *International Journal of Sustainable Built Environment*, *5*(2), 549–563. https://doi.org/10.1016/J.IJSBE.2016.08.004

dos Santos, S. C., Vilela, J. F. F., Carvalho, T. H., Rocha, T. C., Candido, T. B., Bezerra, V. S., & Silva, D. J. (2024). Artificial Intelligence in Sustainable Smart Cities: A Systematic Study on Applications, Benefits, Challenges, and Solutions. *International Conference on Enterprise Information Systems, ICEIS - Proceedings*, *1*, 644–655. https://doi.org/10.5220/0012617900003690

Golubchikov, O., & Thornbush, M. (2020). Artificial intelligence and robotics in smart city strategies and planned smart development. *Smart Cities*, *3*(4). https://doi.org/10.3390/smartcities3040056

Golubchikov, O. (2020, December). *People-smart sustainable cities*. Researchgate

https://www.researchgate.net/publication/347442407_People-Smart_Sustainable_Cities

Gomstyn, A., & Jonker, A. (2023). *What is a smart city?* Ibm. https://www.ibm.com/think/topics/smart-city

Greater London Authority (2018). *Smarter London together & the mayor's roadmap to transform London into the smartest city in the world*. https://www.london.gov.uk/sites/default/files/smarter_london_together_v1.66_-_published.pdf

Handan, İ. I. (2021, 31 Temmuz). *Top five industries that will gain the most from digital twin applications in 2021.* Dijitalis. https://dijitalis.com/blog/2021de-dijital-ikiz-uygulamalari-ile-en-buyuk-kazanc-saglayacak-ilk-bes-sektor/

Ivanov, S., Nikolskaya, K., Radchenko, G., Sokolinsky, L., & Zymbler, M. (2020). Digital twin of city: Concept overview. *Proceedings - 2020 Global Smart Industry Conference, GloSIC 2020*, 178–186. https://doi.org/10.1109/GloSIC50886.2020.9267879

José, R., & Rodrigues, H. (2024). A Review on Key Innovation Challenges for Smart City Initiatives. *Smart Cities*, *7*(1), 141–162. https://doi.org/10.3390/smartcities7010006

Karri, C., Machado, J. J. M., Tavares, J. M. R. S., Jain, D. K., Dannana, S., Gottapu, S. K., & Gandomi, A. H. (2024). Recent Technology Advancements in Smart City Management: A Review. *Computers, Materials and Continua*, *81*(3), 3617–3663. https://doi.org/10.32604/cmc.2024.058461

Khan, U. T., & Zia, M. F. (2021). Smart city technologies, key components, and its aspects. *4th International Conference on Innovative Computing, ICIC 2021*. https://doi.org/10.1109/ICIC53490.2021.9692989

Kumaş, E., & Erol, S. (2021). Endüstri 4.0'da anahtar teknoloji olarak dijital ikizler. *Politeknik Dergisi*, *24*(2), 691–701. https://doi.org/10.2339/politeknik.778934

Leng, J., Wang, D., Shen, W., Li, X., Liu, Q., & Chen, X. (2021). Digital twins-based smart manufacturing system design in Industry 4.0: A review. *Journal of Manufacturing Systems*, *60*, 119–137. https://doi.org/10.1016/J.JMSY.2021.05.011

Lohmann, R., & Van der Zwaan, S. (n.d.). *Automation and Smart Cities: Opportunity or threat?* www.2getthere.eu

Metropolitan Municipalities Law No. 5216, (2004) *Article 7, Article 9, Article 21* https://www.mevzuat.gov.tr/mevzuat?MevzuatNo=5216&MevzuatTur=1&MevzuatTertip=5

Michelucci, F. V., De Marco, A., & Tanda, A. (2016). Defining the Role of the Smart-City Manager: An Analysis of Responsibilities and Skills. *Journal of Urban Technology*, *23*(3), 23–42. https://doi.org/10.1080/10630732.2016.1164439

Municipalities Law No. 5393, (2005) *Article 18* *https://www.mevzuat.gov.tr/mevzuat?MevzuatNo=5393&MevzuatTur=1&MevzuatTertip=5*

Presidential Decisions (2018). *2018/30474 Decree Law* https://www.resmigazete.gov.tr/eskiler/2018/07/20180710.pdf

Presidency of the Republic of Türkiye, Strategy and Budget Directorate (2023). *Türkiye's Twelfth Development Plan (2024-2028)* https://www.sbb.gov.tr/wp-content/uploads/2023/12/On-Ikinci-Kalkinma-Plani_2024-2028_11122023.pdf

Proptechos (n.d.). *These cities are best prepared for a 'smart city' future. technology is developing faster than ever before. But are our cities keeping up?* https://proptechos.com/smart-city-index/

PwC (2022). *How digital twins can make smart cities better.* https://www.pwc.com/m1/en/publications/documents/how-digital-twins-can-make-smart-cities-better.pdf

Puttkamer, L. (2023, 29 Jun). *Smart city london: europe's smartest city.* Bee smart city.

https://www.beesmart.city/en/smart-city-blog/london-europes-smartest-city

Republic of Türkiye Istanbul Metropolitan Municipality Information Technology Department Smart City Branch Directorate. (2021) *2030 istanbul smart city strategic plan.* *https://www.akillisehir.istanbul/wp-content/uploads/2024/03/2030_Istanbul_Akilli_Sehir_Stratejik_Plani.pdf*

Republic of Türkiye Ministry of Environment and Urbanization (2019). *Türkiye's Ministry of Environment, Urbanization and Climate Change 2020-2023 National Smart Cities Strategy and Action Plan https://www.akillisehirler.gov.tr/wp-content/uploads/EylemPlani.pdf*

Roth, Z., & Incera, M. (2024, May 18). *The Rise of AI-Powered Smart Cities*. https://www.spglobal.com/en/research-insights/special-reports/ai-smart-cities

Shahat, E., Hyun, C. T., & Yeom, C. (2021). City digital twin potentials: A review and research agenda. In *Sustainability (Switzerland)* (Vol. 13, Issue 6). MDPI AG. https://doi.org/10.3390/su13063386

Smart cities portal (n.d.) *National smart cities open data portal launched* https://www.akillisehirler.gov.tr/2023/05/15/ulusal-akilli-sehirler-acik-veri-portali-acildi/ accessed on 28 November 2024

Szpilko, D., Naharro, F. J., Lăzăroiu, G., Nica, E., & de la Torre Gallegos, A. (2023). Artificial intelligence in the smart city - a literature review. *Engineering Management in Production and Services*, *15*(4), 53–75. https://doi.org/10.2478/emj-2023-0028

The Provincial Administration Law No. 5442, (1949) *Article 9, Article 21* *https://www.mevzuat.gov.tr/mevzuat?MevzuatNo=5442&MevzuatTur=1&MevzuatTertip=3*

Trindade, E. P., Hinnig, M. P. F., da Costa, E. M., Marques, J. S., Bastos, R. C., & Yigitcanlar, T. (2017). Sustainable development of smart cities: a systematic review of the literature. *Journal of Open Innovation: Technology, Market, and Complexity*, *3*(3), 1–14. https://doi.org/10.1186/S40852-017-0063-2

Türkiye's Twelfth Development Plan (2024-2028). https://www.sbb.gov.tr/wp-content/uploads/2023/12/On-Ikinci-Kalkinma-Plani_2024-2028_11122023.pdf

Wolniak, R., Gajdzik, B., Grebski, M., Danel, R., & Grebski, W. W. (2024). Business Models Used in Smart Cities—Theoretical Approach with Examples of Smart Cities. *Smart Cities*, *7*(4), 1626–1669. https://doi.org/10.3390/smartcities7040065

Wolniak, R., & Stecuła, K. (2024). Artificial Intelligence in Smart Cities—Applications, Barriers, and Future Directions: A Review. *Smart Cities*, *7*(3), 1346–1389. https://doi.org/10.3390/smartcities7030057

Yang, S., Jahanger, A., & Usman, M. (2024). Examining the influence of green innovations in industrial enterprises on China's smart city development. *Technological Forecasting and Social Change*, *199*, 123031. https://doi.org/10.1016/J.TECHFORE.2023.123031

Yıkıcı, A. (2023). Dijital İkiz Şehir Fenomeni: Dünyadan Örnekler ve Türkiye'deki Yönelimler. *Kent Akademisi Dergisi*, *16*(1), 138–163. https://doi.org/10.35674/kent

Zara S. (2023, February 22). *FIVE Automation Technologies for Smart Cities*. https://kahedu.edu.in/five-automation-technologies-for-smart-cities/

Paper #67

Title: Nagorno-Karabakh Crisis: An Evaluation from the Perspective of Social Media Analytics.

Author(s): Burak Arslan & Emrah Aydemir.

Abstract:
Following Russia's policies after 1828 and the migration of Armenian populations to the Karabakh region, the Azerbaijani population began to become a minority. The first large-scale Karabakh conflict between Armenia and Azerbaijan began in 1905, with the most recent war taking place in 2020. The technological revolution between these periods of war has brought the battlefield to social media platforms in the present day. This study is based on the research question of whether it is possible to analyze a war by aggregating a large number of user comments on social media during the war. In this context, a total of 616,696 data entries from X were collected between 27.09.2020 and 09.11.2020, each containing at least one of the keywords "Qarabağ" (Azerbaijani), "Karabakh" (English), or "Karabağ" (Turkish). The study uses text mining techniques to analyze the diversity and prominence of topics expressed by users on social media during the war. The findings of the study show that Azerbaijan continued its struggle not only on the battlefield but also on social media.

Keywords: Nagorno-Karabakh, Armenia-Azerbaijan War, Conflict, Information Warfare, Text Mining, & Social Media Analysis

Öz

1828 yılından sonraki Rusya politikası ile Ermeni unsurların Karabağ bölgesine göçleri sonucu Azerbaycan nüfusu azınlık olmaya başlamıştır. Ermenistan ve Azerbaycan arasındaki ilk büyük çaplı Karabağ çatışması ilk kez 1905 yılında olmuş ve son savaş da 2020 yılında gerçekleşmiştir. Bu savaşlar arasındaki dönemde yaşanan teknolojik devrim, günümüzde savaş alanını sosyal media platformlarına taşımıştır. Bu araştırma bir savaşın, savaş sırasında sosyal medyada yapılan çok sayıda kullanıcı yorumunun bir araya getirilmesi ile analiz edilip edilemeyeceği sorusu üzerine kuruludur. Bu bağlamda Qarabağ (Azerice), Karabakh (İngilizce) ya da Karabağ (Türkçe) kelimelerinden herhangi birini içeren 27.09.2020-09.11.2020 tarihleri arasında toplam 616.696 adet X verisi elde edilmiştir. Araştırmada, savaş sırasında kullanıcıların sosyal medyada dile getirdiği konuların çeşitliliğini ve öne çıkan temaları analiz etmek için metin madenciliği teknikleri kullanılmıştır. Araştırmanın bulguları Azerbaycan'ın savaşta yalnızca sahada değil, sosyal medyada da mücadeleye devam ettiğini göstermektedir.

Keywords: Dağlık Karabağ, Karabağ Krizi, Azerbaycan Ermenistan Savaşı, Bilgi Savaşı, Metin Madenciliği, Sosyal Medya Analizi

Abstract

Following Russia's policies after 1828 and the migration of Armenian populations to the Karabakh region, the Azerbaijani population began to become a minority. The first large-scale Karabakh conflict between Armenia and Azerbaijan began in 1905, with the most recent war taking place in 2020. The technological revolution between these periods of war has brought the battlefield to social media platforms in the present day. This study is based on the research question of whether it is possible to analyze a war by aggregating a large number of user comments on social media during the war. In this context, a total of 616,696 data entries from X were collected between 27.09.2020 and 09.11.2020, each containing at least one of the keywords "Qarabağ" (Azerbaijani), "Karabakh" (English), or "Karabağ" (Turkish). The study uses text mining techniques to analyze the diversity and prominence of topics expressed by users on social media during the war. The findings of the study show that Azerbaijan continued its struggle not only on the battlefield but also on social media.

Keywords: Nagorno Karabakh, Karabakh Conflict, Armenia-Azerbaijan War, Information Warfare, Text Mining, Social Media Analysis

Introduction

The Nagorno-Karabakh region, located between Iran, Azerbaijan, and Armenia, holds a strategic position as a key access point to the Caucasus. This has led to continuous struggles among regional states to claim the area throughout history (Aras 113-22). Having hosted various Turkish civilizations for centuries, the region is also rich in natural resources (Kuduban and Kaya 925). A historical analysis of Karabakh reveals its predominantly Turkish and Muslim population to the extent that even Russia recognized it as a Turkish homeland (Erarslan and Özdemir 315-34). With treaties signed in the 19th century, Russia began asserting control over the region. Despite the Turkish majority at the time, Russia aimed to suppress this demographic by relocating Armenians from Anatolia and Iran to the area (Kuduban and Kaya 925)

In the 1920s, the Soviet Union confirmed that the region belonged to Azerbaijan. By the 1980s, as the Soviet Union began to collapse, Armenia sought to claim rights over the Nagorno-Karabakh region, taking advantage of the political instability. This reflected Armenia's ambition to realize its "Greater Armenia from sea to sea" ideology by asserting control over the region (Erarslan and Özdemir 315-34).

Armenia and Azerbaijan, located in the South Caucasus region, are former Soviet Union countries. The disputes between Armenia and Azerbaijan date back to the late stages of the Ottoman Empire's collapse. With the dissolution of the Soviet Union, conflicts between the two countries began. Over the years, several wars have occurred in the Nagorno-Karabakh region, leading to a history filled with conflict (Khan 28). One of the arguments raised regarding the Nagorno-Karabakh issue is that both countries claim to have previously existed in the region (Sapmaz and Sarı 6). This can be seen as an analysis of the ongoing wars in the region.

Until the dissolution of the Soviet Union, Turkey considered the issue in this region as an internal matter of the concerned country. Turkey's peaceful approach at this point strengthened the Armenians' desire to claim ownership of the region. Armenia always acted with the belief that Russia was behind its actions in this region. Another neighboring state, Iran, supported Armenia covertly to serve its interests, which shows that Azerbaijan had no support in this war except Turkey (Kuduban and Kaya 928).

The first serious tension between Armenia and Azerbaijan occurred in 1988. This marked the beginning of occupation activities against Azerbaijani Turks in the region. Specifically, during the period of February 25 and 26, 1992, the Khojaly massacre, in which more than 600 Azerbaijani Turks were killed with the support of a Russian regiment stationed in the region, is considered a clear example of genocide. During the First Nagorno-Karabakh War, which took place between 1988 and 1994, over 32,000 Azerbaijani civilians and around 16,000 soldiers were massacred (Erarslan and Özdemir 315-34).

The Minsk Group, established to resolve the Nagorno-Karabakh issue, was given co-chairmanship by the United States, Russia, and France in 1994, ensuring that these countries would play a leading role in solving the problem. Despite these countries coming together to maintain peace in the region, no significant progress has been made in terms of peace. Both countries continue to claim ownership of the Nagorno-Karabakh region, and negotiations on resolving the issues in this area have been ongoing for twenty-five years. One of the biggest factors during this process has been the forced migration of the people living in the region due to the unrest in the area (Khan 29-30).

In 1991, Azerbaijan gained independence and directly linked the Nagorno-Karabakh region, an autonomous area, to its central government. This led the Armenians in the region to declare independence as well. With the change in the Azerbaijani government, the Armenians, supported by Russia, occupied Azerbaijani territories between 1993 and 1994. The Azerbaijani government has expressed that the Minsk Group, co-chaired by Russia, the USA, and France, exhibited a biased stance regarding the Nagorno-Karabakh issue. What justifies Azerbaijan's position is that three of the countries that rejected the proposal for the return of lands unlawfully seized by the Armenians were members of these states (Sapmaz and Sarı 4-6). The occupations continued until 1994 when a ceasefire agreement was signed between the two states. By the time of the ceasefire, 20% of Azerbaijan's territory had been occupied, and nearly one million Azerbaijani Turks were forced to migrate to Baku (Shamilov and Kara 113).

The difficulties experienced in the governance of Azerbaijan until 1994 were reflected on the battlefield as well. As a result, many regions of Azerbaijan's territory were occupied by Armenia until the first ceasefire. The Bishkek Protocol, which came into effect with the ceasefire, temporarily suspended the issues in the region. At the same time, a multinational military force was deployed to the area to ensure security. After the ceasefire, Azerbaijan fell into internal turmoil. It experienced a coup, while Armenia, with the support it received, worked on the development of the Nagorno-Karabakh region it had occupied. Furthermore, the lack of identity and passport control in the areas separated from Azerbaijan led to uncontrolled crossings into the region. These processes made it clear that Azerbaijan's diplomatic efforts to regain the lost territories would be very challenging (Jazeera 1).

The failure of Western-established structures aimed at resolving the Nagorno-Karabakh conflict made Azerbaijan believe that the issue could only be solved on the battlefield. For this reason, Azerbaijan developed its military with support from Turkey. To reclaim the territories it had lost, Azerbaijan explored various avenues. It stated that, within the framework of the military doctrine adopted in 2010, it would utilize all diplomatic, military, and political options to resolve the issue. During this process, Armenia launched short-term attacks to expand the territories it had occupied, further escalating the tensions in the region. One of these attacks was the 2016 Four-Day War. Azerbaijan managed to liberate several strategically important areas from Armenian occupation in this war, reigniting hope of regaining the previously lost territories (Erarslan and Özdemir 325).

The war, known as the Four-Day War, took place in April 2016. At this point, Azerbaijan made a significant decision and chose the path of war. The conflict began on April 1 and ended on April 5. This war is considered the worst conflict since the 1994 ceasefire. The reasons for the resumption of the war include Azerbaijan's dissatisfaction with the Minsk Group, which was created to end the conflict but had not taken concrete steps toward peace, and Azerbaijan's desire to demonstrate its military strength to its people, keeping its motivation alive. Additionally, Azerbaijan initiated the war to assess its military capabilities and to see how Armenia would respond (Ali 55). Through these actions, Azerbaijan adopted a different strategy compared to its stance between 1990 and 1994.

The election of Nikol Pashinyan in 2018, following the Velvet Revolution in Armenia, and his portrayal as pro-American increased expectations for a potential change in the region. However, the anticipated closer relationship with Western countries was not achieved during this process, and Russia's dominant influence over Armenia continued. With Pashinyan's rise to power, the expectations for economic improvement were also dashed, and Armenia's economy entered a severe crisis (Çalışkan 1). As tensions between the two countries continued to rise, Pashinyan stated in a speech, "Nagorno-Karabakh is Armenia's," to which Aliyev responded, "Nagorno-Karabakh is Azerbaijan's!" — an exchange that inevitably escalated tensions (Erarslan and Özdemir 325).

The long-standing tensions between Azerbaijan and Armenia, along with Armenia's continuous violations of the ceasefire in an attempt to expand the territories it occupied, led the Azerbaijani government to break its silence and launch a counteroffensive. The war, which reignited on September 27, 2020, lasted approximately 44 days. Despite Armenia's support from Western countries, it could not withstand Azerbaijan's military strength. With a much more prepared army compared to the 1990-1994 period and the support of Turkey, Azerbaijani forces dealt a decisive blow to Armenian troops. Armenia withdrew from the occupied regions, and a ceasefire agreement became necessary. Through this ceasefire, Azerbaijan regained its lost territories, and the city of Shusha, which was of significant importance to Azerbaijan, was liberated from Armenian control and brought under Azerbaijani sovereignty. Following this, the "Triple Declaration" was signed, which called for the withdrawal of Armenian forces from the remaining parts of Nagorno-Karabakh, as well as the establishment of a military monitoring center by Turkish and Russian forces for regional security. As a result of this war, Azerbaijan justified its resistance not only on the military front but also diplomatically. Azerbaijan's firm stance in diplomacy over many years was one of the main factors that led to a favorable outcome for Azerbaijan. While Azerbaijan gained international respect, Armenia's identity as an occupying force became recognized on the global stage. By defeating Armenia at the end of the war, Azerbaijan demonstrated that it could reclaim the territories occupied by Armenia with its military force. However, the global community has recognized Azerbaijan's consistent efforts to seek a diplomatic solution without resorting to war. During the conflict, even in the face of attacks on civilians by the opposing side, Azerbaijan never adopted such a stance and refrained from crossing the boundaries of warfare (Hasanoğlu et al. 522-29). Azerbaijan successfully resolved the Nagorno-Karabakh issue, which had remained unresolved by the Minsk Group and other European Union groups, through the peace treaty signed on November 9, 2020. Turkey's support during the war is an undeniable fact. At this point, messages of support from Turkish officials, including the president and ministers, clearly conveyed that the Turkish nation stood by Azerbaijan (Khan 30).

This war was conducted not only on the battlefield but also on social media platforms, leveraging the opportunities provided by modern technology. As a result, there has been an opportunity to analyze a war through technology. How this long-standing crisis has affected the audiences following the war on social media platforms has become a subject of interest. This study aims to explore the reflection of societal events, which have deeply permeated digital platforms, on the social media platform X. In this context, the research question revolves around whether it is possible to analyze a war by collecting many user comments on social media during the war. The rest of the study seeks to answer this research question. Being the first study to approach the Nagorno-Karabakh issue from a social media perspective, this research highlights its originality.

Literature Review

With years having passed since the first Nagorno-Karabakh war, significant changes have occurred worldwide. Analyzing the course of the war, it becomes evident that social media platforms were effectively utilized (Mevlütoğlu 1). The rapid advancement of technology, unprecedented in history, has significantly developed social media over the past two decades, making it inevitable for warring states to incorporate this phenomenon into their strategies. During the Nagorno-Karabakh war, both nations used social media as a weapon. By announcing unverified false victories and implying the commission of war crimes, efforts were made to attract international attention. At the same time, local populations shared information through social media, increasing awareness of the situation. Throughout the war, numerous images, videos, and comments were shared on social media platforms, contributing to understanding the necessary military equipment and strategic positioning of forces (Johnston 15). "In particular, Azerbaijan's publication of footage from UAV and kamikaze drone strikes provided a significant psychological advantage" (Mevlütoğlu 1).

The information shared on social media is not always accurate and may contain manipulative discourse. During the Nagorno-Karabakh war, a significant amount of misinformation was disseminated on social media platforms, influencing public perception. In this context, Dardari et al. (1-59) analyzed the use of misinformation and hate speech across social media platforms such as Twitter, Facebook, VK, and Instagram before, during, and after the Nagorno-Karabakh war, examining how these platforms addressed such issues. Dardari et al. (5) stated that tracing the sources of manipulative comments and misinformation is highly time-consuming. Despite the platforms' comprehensive policies prohibiting hate speech, they struggle to manage it effectively. They noted that identifying such content remains challenging due to the sheer volume of posts containing direct hate speech. However, they were able to detect hate speech and fabricated posts shared by Armenian users, as well as similar content from Azerbaijani users. In another study analyzing user comments during the war on the social media platform YouTube, Söğüt (306-24) found that the comments from users of both states contained hate speech, similar to the findings of Dardari et al. (5). The researchers highlighted that Azerbaijani users' discourse was primarily centered on revenge. In contrast, Armenian users' comments extended to religious and ethnic narratives. This demonstrates the role of social media data in analyzing societal reactions during crises. Focusing on the role of social media in the transmission of historical events, Johnston (15) emphasized that while social media served as a crucial information tool during the Nagorno-Karabakh war, the significance of platform usage and the ability of social media data to reveal the background of events that directly affect societies have not been sufficiently considered.

However, some studies examine historical events from a social media perspective. This section includes previous research in which crises have been analyzed using social platform data. Studies leveraging this rich data source to gain insights into current events have become more prevalent in the literature in recent years. One such study by Öztürk and Ayvaz (136-47) analyzed public opinion on the Syrian refugee crisis in 2018. The researchers collected 2,381,297 user comments from the X platform. After applying preprocessing steps to the dataset, they found that only 348,707 user posts were suitable for analysis. The study revealed that user-generated Turkish content differed significantly from English content. While Turkish-language posts were more moderate (positive) toward the Syrian refugee crisis, English-language posts tended to be more neutral or negative. Despite the crisis occurring within Turkey's borders, Turkish social media users displayed a more optimistic perspective. Despite the crisis occurring within Turkey's borders, Turkish social media users displayed a more optimistic perspective. In a similar study, Lee et al. (10033-48) analyzed global reactions to the Taliban's takeover of Afghanistan in 2021 using social media user data. The study utilized geotagged posts, identifying India, the United States, the United Kingdom, Pakistan, and Afghanistan as the top countries generating content on the topic. Notably, negative user-generated content was predominantly from India and the United States, while positive sentiment was more common in posts from Pakistan and Afghanistan. The analysis results indicated that a significant portion of the Afghan population expressed approval of the Taliban's takeover.

Social media platform data serves as a rich source of information and, when utilized correctly, can play a crucial role in uncovering various details. This study, which analyzes user-generated data from a social media platform regarding the Nagorno-Karabakh war, offers a unique contribution to the literature by examining the course of the war from the perspective of platform users and by employing a distinctive methodological approach in its analysis.

Methodology

The widespread use of online platforms has led to the generation of vast amounts of digital textual data left by users on social media platforms, blogs, online newspapers, and e-commerce sites. One widely used platform is X, formerly known as Twitter, which hosts many user comments under hashtag topics. In this context, data was collected from users on the X platform who posted in Turkish and Azerbaijani during the Karabakh war. A total of 616,297 user-generated posts containing the keywords Qarabağ (Azerbaijani), Karabakh (English), or Karabağ (Turkish) were gathered within the 44 days from the start of the war on September 27, 2020, to its conclusion on November 10, 2020. In the next phase of the study, text mining techniques were employed. The analysis was conducted using topic modeling, one of the key processes in text mining.

Data Preprocessing

Data obtained from social media is unstructured. Text mining and natural language processing (NLP) techniques transform unstructured data into structured data (Kumar et al. 1-2). The preprocessing phase, often overlooked in text mining, is one of the most crucial steps (García et al. 7). During this phase, text data is cleaned and organized to prepare it for further analysis. Duplicate posts, hashtags, emojis, numbers, and other characters that do not add semantic value to the data, are removed. This process ensures standardization among the data. After preprocessing, the dataset was refined to 430,091 standardized user posts for further analysis. By eliminating meaningless characters from the text data, the goal was to enhance the accuracy of the next phase of topic modeling (Haddi et al. 27).

Topic Modeling

Topic modeling, a technique used in text mining, aims to uncover the latent semantic relationships within large text corpora (Kherwa and Bansal 1). It is particularly significant to analyze extensive groups of social media posts to identify recurring themes (Churchill and Singh 1). In the topic modeling process, which utilizes machine learning, theme categories were first determined. This allowed user-generated content to be classified under predefined themes. These themes were derived from a literature review where:

- "Sharing Information" was selected based on Johnston's (15) emphasis on the role of social media in information dissemination.
- "Insult" was included following Söğüt (324-26), who found that both sides of the Karabakh conflict used hate speech.
- "Brotherhood" was based on Khan (27-34), who highlighted Turkey's consistent support for Azerbaijan.
- "Rightfulness" was inspired by Erarslan and Özdemir (315-34), who provided evidence supporting Azerbaijan's rightful claim.
- "Celebration" was added to reflect the impact of the war's conclusion on users.

A subset of 1,000 user posts was manually labeled based on relevant keywords matching these themes. During classification, posts that fit only one theme were assigned a binary label, while posts covering multiple themes underwent multi-label classification (Güner et al. 7). The labeled text data was then converted into numerical (vectorized) format. A machine learning model was trained using these vectorized datasets, allowing the algorithm to classify all user-generated content into predefined themes. As a result, valuable insights were obtained regarding public perception and discourse surrounding the conflict.

Findings

Table 1
The language of posts made by all X users, including Azerbaijani and Turkish X user accounts

Language	Post	Azerbaijani User Account	Turkish User Account
en	312.043	311.008	1.035
tr	191.345	12.920	178.425
az	58.411	49.188	9.223
fr	23.914	23.901	13

During the war, posts were shared in 103 languages by X platform users. This indicates that the global agenda closely followed the event. Among the 616,297 posts, the top seven most-shared languages were as follows: 312,043 posts in English, 191,345 posts in Turkish, 58,411 posts in Azerbaijani, and 23,914 posts in French. These were followed by Russian, Italian, Portuguese, and Spanish. As previously mentioned, the user data obtained in the study was from Turkish and Azerbaijani user accounts. In this context, the languages and numbers of posts shared by user accounts of the two different nations on the X platform can be seen in Table 1. Azerbaijani users shared a total of 427,415 posts accounts in 103 different languages, and 189,281 posts were shared by Turkish user accounts in 39 different languages. As shown in Table 1, the most frequently shared languages by Turkish user accounts were Turkish, Azerbaijani, and English. In contrast, the most frequently shared languages by Azerbaijani user accounts were English, Azerbaijani, French, and Turkish. Turkish users used their native language more frequently than Azerbaijani users when sharing posts. This may be interpreted as an effort by the Turkish people to express their solidarity with the Azerbaijani people during the crisis. On the other hand, the language predominantly used in posts shared by Azerbaijani user accounts was English. This suggests that Azerbaijani social media users preferred English, a global language, to communicate the war situation to the world more clearly and directly.

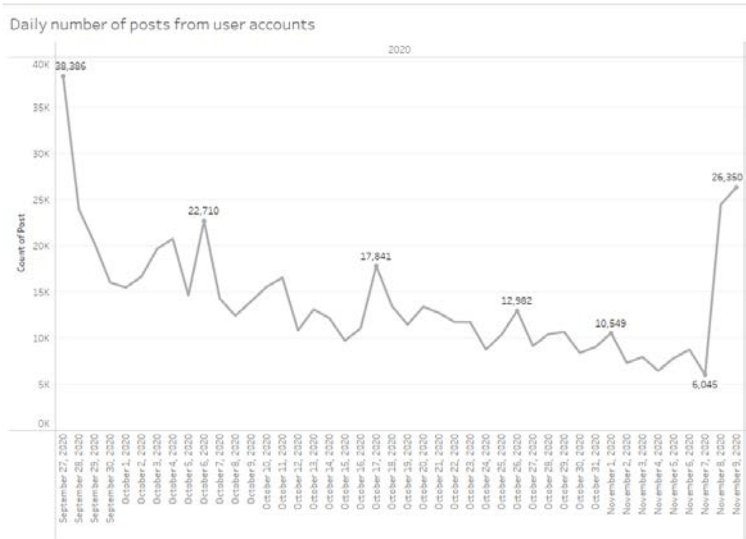


Figure 1. Daily number of posts from user accounts

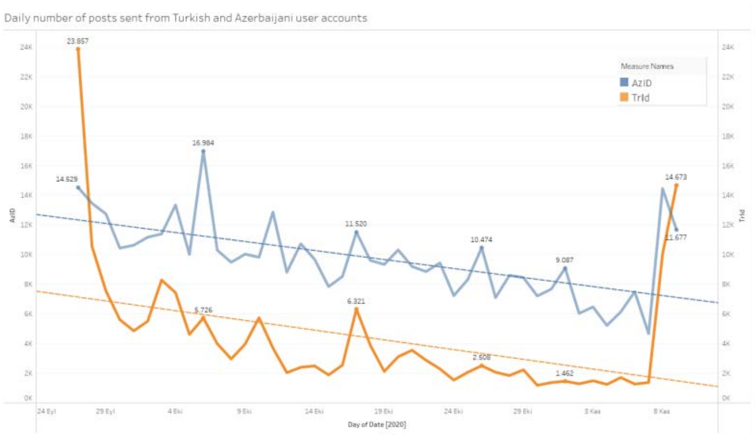


Figure 2. Daily number of posts sent from Turkish and Azerbaijani user accounts

In the graph shown in Figure 1, it can be observed that although all user accounts shared a very high number of posts during the first days of the war, the number gradually decreased over time, with the number of posts on the last day approaching the peak observed on the first day. A downward trend is observed throughout the process when both figures are examined. Based on this, it can be stated that while users reacted strongly in the initial moments of the event, the reactions decreased after a certain period as the events were accepted. However, when the graphs are analyzed, it is observed that the number of posts increased again on specific dates. One of these dates is October 6, 2020, when the United Nations renewed its call to immediately cease the conflict (Yürük 1). Additionally, on the evening of October 5, the United States, Russia, and France made a joint ceasefire call regarding the Nagorno-Karabakh issue (Euronews 1). In Figure 2, a detailed view of the Azeri and Turkish social media accounts clearly shows that both account types reacted to the relevant news, as seen in the change in the number of posts. A 70% increase in posts from Azeri user accounts was observed compared to the previous day, while Turkish user accounts saw a 24% increase. Other dates when user posts peaked include October 10, October 17, and October 26, when news of ceasefire agreements between the two countries was shared; however, these agreements were broken each time (Bayar; Guardian; Sharago). As seen in Figure 2, each new piece of news pushed users to share posts. Although users' responses to the shared news are clearly visible, the intensity of their reactions decreased over time.

Category	Accuracy	Recall	Precision	F1
Insult	0,85	0,7917	0,8837	0,8352
Rightfulness	0,8596	0,8214	0,8846	0,8519
Sharing_Information	0,8854	0,8571	0,878	0,8675
Brotherhood	0,9143	0,8462	0,9778	0,9072
Celebration	0,951	0,9149	0,9773	0,9451

Table 2. Classification Results

The accuracy of the machine learning model in predicting the identified themes, based on the numerical transformation of the user data, is shared in Table 2. The trained machine learning model was used to classify 430,091 user data points into the identified topics. As a result, the graphical representation of the changes in the underlying factors of the reactions of X platform users to the event between 27.09.2020 and 09.11.2020 is shown in Figure 5.

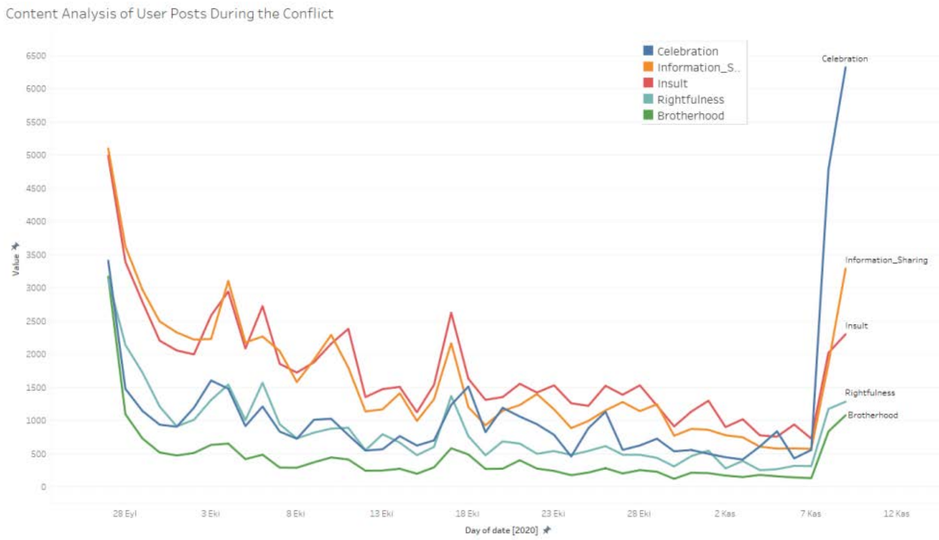


Figure 5. Content Analysis of User Posts During the Conflict

As shown in Figure 5, from the moment the conflict began until its final stage, the X platform became a space for information sharing. The number of posts containing information has consistently been higher than other categories throughout the war, to keep the focus on the war elevated, whether the information was accurate or manipulative. On October 8, 2020, a Russian social media account shared images of a bombing claimed to be related to the Nagorno-Karabakh war. However, the shared images were taken from a video game and circulated on multiple social media platforms. These images were even shared in India, claiming that Armenia had shot down Azerbaijani planes (BBC, 2020). Among X platform users, the message "check this russian high profile propagandist vladimir solovyov using arma game video his live stream and saying these are stream from nagorno karabakh war" was shared to announce that the images were fabricated. These findings support Johnston’s research.

The interest of Turkish social media users in the Nagorno-Karabakh war has been reflected in user posts with messages such as "Turkey stands by its brother Azerbaijan in its rightful cause, Qarabağ is Azerbaijan's." This highlights the brotherhood between the two nations and the emphasis on Azerbaijan's rightful cause. Celebration-oriented user posts have also been shared since the early stages of the conflict, which can be interpreted as an effort to establish psychological dominance on social media. Beyond these, it has been observed that users shared numerous hate-filled posts throughout the course of the war.

Conclusion

This study analyzes the Nagorno-Karabakh war from a socio-technical perspective, evaluating the war process through social media. In this context, the user comments shared by Azeri and Turkish user accounts on the X platform regarding the Nagorno-Karabakh war were analyzed. The preference of Azeri users for English in their posts indicates an effort to raise global awareness about the war. Throughout the conflict, a significant amount of information was shared, and it was found that users were prepared for the manipulative information being spread. Furthermore, numerous hate-filled posts were also shared, and the X platform became not only a source of information sharing but also a platform that spread hate speech. Users tended to misuse the anonymity provided by social media platforms rather than expressing their justification for the issue. As a result, Azerbaijan's rightful cause was discussed less on the social media front. While there were social media users who maintained the motivation to win the war from the beginning until the end, this study shows that the longer a crisis lasts, the more likely users are to adapt to or accept the situation. By addressing a historical topic from a technical perspective, this research has demonstrated that approaching crises affecting societies with big data can uncover many hidden details. The findings from this research serve as an important resource for field experts and historians in future studies.

Resources

Ali, A. "The Nagorno Karabakh Conflict-the Beginning of the Soviet End." *Retrieved from ResearchGate: https://www. researchgate. net/publication/339415817_The_Nagorno_Karabakh_Conflict-_The_Beginning_of_the_Soviet_End*, 2020.

Aras, Osman Nuri. "Ekonomik Ve Siyasi Sonuçları Bakımından Hocalı Katliamı Ve Karabağ Sorunu." *Fırat Üniversitesi Orta Doğu Araştırmaları Dergisi*, vol. 9, no. 2, 2015, pp. 113-22.

Bayar, Gözde. "Bm, Azerbaijan, Armenia Agree on Cease-Fire Starting Monday." AA https://www.aa.com.tr/en/azerbaijan-front-line/azerbaijan-armenia-agree-on-cease-fire-starting-monday/2018915. Accessed 26 October 2020.

Churchill, Rob and Lisa Singh. "The Evolution of Topic Modeling." *ACM Computing Surveys*, vol. 54, no. 10s, 2022, pp. 1-35.

Çalışkan, Burak. "Azerbaycan-Ermenistan Çatışması Ve Türkiye'ye Yansımaları." INSAMER https://www.insamer.com/tr/azerbaycan-ermenistan-catismasi-ve-turkiyeye-yansimalari_3110.html. Accessed 20 July 2020.

Dardari, Aya et al. "Social Media, Content Moderation and International Human Rights Law: The Example of the Nagorno-Karabakh/Artsakh Conflict." *The Promise Institute for Human Rights at UCLA School of Law, https://promiseinstitute. law. ucla. edu/wpcontent/uploads/2022/05/Social-Media-Content-Moderation-and-Internationals-Human-RIghts-Law. pdf, retrieved on April*, vol. 11, 2024.

Erarslan, Fatih and Fatma Nur Özdemir. "Azerbaycan-Türkiye İlişkilerinde Önemli Bir Kavşak: İkinci Karabağ Savaşi." *Türk Dünyası Araştırmaları*, vol. 129, no. 255, 2021, pp. 315-34.

Euronews. "Abd, Rusya Ve Fransa'dan Dağlık Karabağ Için Ortak Ateşkes Çağrısı." https://tr.euronews.com/2020/10/05/abd-rusya-ve-fransa-dan-dagl-k-karabag-icin-ortak-ateskes-cagr-s. Accessed 5 October 2020.

García, Salvador et al. *Data Preprocessing in Data Mining.* vol. 72, Springer, 2015.

Guardian. "Nagorno-Karabakh: Armenia and Azerbaijan Agree to Ceasefire." The Guardian https://www.theguardian.com/world/2020/oct/10/nagorno-karabakh-armenia-and-azerbaijan-agree-to-ceasefire. Accessed 10 October.

Güner, Samet et al. "Service Quality in Rail Systems: Listen to the Voice of Social Media." *Transportation Research Record*, vol. 2678, no. 6, 2024, pp. 824-47.

Haddi, Emma et al. "The Role of Text Pre-Processing in Sentiment Analysis." *Procedia computer science*, vol. 17, 2013, pp. 26-32.

Hasanoğlu, Murteza et al. "İkinci Karabağ Savaşı Sonrası Azerbaycan-Türkiye İlişkileri." *Uluslararası Yönetim Akademisi Dergisi*, vol. 3, no. 3, 2020, pp. 522-29.

Jazeera, Al. "Öncesi Ve Sonrasıyla Karabağ Savaşı." *Al Jazeera*, 2020. https://www.aljazeera.com.tr/dosya/oncesi-ve-sonrasiyla-karabag-savasi.

Johnston, Brant. "Social Media: The New Intelligence Collection Platforms." *United Service*, vol. 72, no. 4, 2021, pp. 15-16.

Khan, Mumim Ahmad. "The Conflict of Azerbaijan and Armenia with Special Reference to Nagorno Karabakh: An Overview." *Journal of Malay Islamic Studies*, vol. 4, no. 1, 2021, pp. 27-34.

Kherwa, Pooja and Poonam Bansal. "Topic Modeling: A Comprehensive Review." *EAI Endorsed transactions on scalable information systems*, vol. 7, no. 24, 2019.

Kuduban, Duygu Ata and Mevlüt Kaya. "Karabağ Sorununa Uluslararası Güçlerin Yaklaşımları Üzerine Tarihsel Bir Değerlendirme." *21. Yüzyılda Eğitim ve Toplum*, vol. 7, no. 21, 2018, pp. 923-49.

Kumar, Sunil et al. "Applications of Text Mining in Services Management: A Systematic Literature Review." *International Journal of Information Management Data Insights*, vol. 1, no. 1, 2021, p. 100008.

Lee, Ernesto et al. "Inquest of Current Situation in Afghanistan under Taliban Rule Using Sentiment Analysis and Volume Analysis." *IEEE Access*, vol. 10, 2022, pp. 10333-48.

Mevlütoğlu, A. "Dağlık Karabağ Savaşı'na Dair Askeri-Stratejik Gözlemler." Panorama Web Sayfası: https://www. uikpanorama. com/blog/2020/11/05/2020 …, 2020.

Öztürk, Nazan and Serkan Ayvaz. "Sentiment Analysis on Twitter: A Text Mining Approach to the Syrian Refugee Crisis." *Telematics and Informatics*, vol. 35, no. 1, 2018, pp. 136-47.

Sapmaz, Ahmet and Gökhan Sarı. "Dağlık Karabağ Sorununda Azerbaycan Tarafından Kuvvet Kullanım Olasılığının Analizi." *Güvenlik Stratejileri Dergisi*, vol. 8, no. 15, 2012, pp. 1-32.

Shamilov, Gafar and Canan Öykü Dönmez Kara. "Birinci Dağlık Karabağ Savaşı Göçmenlerinin Sosyo-Ekonomik Sorunları: Bakü Binegedi İlçesi Örneği." *Yönetim Bilimleri Dergisi*, vol. 19, no. Özel Sayı, 2021, pp. 107-36.

Sharago, Luke. "Armenia, Azerbaijan Agree to New Ceasefire in Nagorno-Karabakh Conflict." France 24 https://www.france24.com/en/asia-pacific/20201017-armenia-azerbaijan-agree-to-new-ceasefire-in-nagorno-karabakh-conflict. Accessed 17 October 2020.

Söğüt, Fatih. "Dağlik Karabağ Çatişmasi Ve Nefret Söylemi: Youtube Kullanici Yorumlari Üzerine Bir İnceleme." *İnönü Üniversitesi İletişim Fakültesi Elektronik Dergisi (İNİF E-Dergi)*, vol. 6, no. 2, 2021, pp. 306-24.

Yürük, Betül. "Bm, Azerbaycan Ve Ermenistan'a Dağlık Karabağ'da Çatışmalara Derhal Son Verme Çağrısını Yineledi." AA https://www.aa.com.tr/tr/azerbaycan-cephe-hatti/bm-azerbaycan-ve-ermenistana-daglik-karabagda-catismalara-derhal-son-verme-cagrisini-yineledi/1996799. Accessed 6 October 2020.