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ORGANIZATIONAL READINESS FOR ARTIFICIAL INTELLIGENCE WITH SYSTEMATIC MAPPING STUDY IN PUBLIC AND PRIVATE SECTORS

Herwan Abdul Muhyi[1], Arianis Chan[1], Tetty Herawaty[1], Rani Sukamadewi[2*], Arbi Abdul Kahfi[1]
[1] Business Administration, Faculty of Social and Political Science, Universitas Padjadjaran, Indonesia
[2] Logistic Business, Faculty of Social and Political Science, Universitas Padjadjaran, Indonesia
E-mail: herwan@unpad.ac.id; arianis.chan@unpad.ac.id; tetty@unpad.ac.id; rani.sukmadewi@unpad.ac.id; arbi16001@mail.unpad.ac.id

ABSTRACT
Artificial Intelligence (AI) in organization is well-established in practice and has emerged as an exciting research area in recent years. However, no comprehensive review of the literature on organizational readiness for AI has been conducted. The aim of this paper is to map the current state of research of organizational readiness for AI. We conducted a systematic mapping study and found 32 relevant primary studies. Our findings are organised into two aspects. First, systematise and classify existing research in terms of number of papers published, year of publication, type of the research, country of origin, research methods, theories, and framework used. Second, to identify research gaps and propose a research agenda in the future. Most articles published after 2019 are dominated by exploratory, empirical and descriptive research and use qualitative and quantitative methods as an approach to conducting research. However, research on organizational readiness for AI is still often carried out in developed countries. The research contributes a thematic analysis of research variables, factor AI adoption, the results of AI implementation, theory and framework, research gaps in the literature, and an agenda for future research. More academic work needs to be done on organizational readiness for AI to improve conceptual clarity, theory building and development, understanding benefits and value for the business, understanding contextual factors, and critically exploring outcomes.

Keywords: organizational readiness; artificial intelligence; SMS; literature review

KESIAPAN ORGANISASI TERHADAP ARTIFICIAL INTELLIGENCE MENGGUNAKAN SYSTEMATIC MAPPING STUDY

ABSTRAK
Praktik penggunaan Artificial Intelligence (AI) dalam organisasi semakin kuat dan telah muncul sebagai bidang penelitian yang menarik dalam beberapa tahun terakhir. Namun, belum ada tinjauan komprehensif literatur mengenai kesiapan organisasi dalam menghadapi AI. Tujuan dari penelitian ini adalah untuk memetakan kondisi penelitian terkini mengenai kesiapan organisasi terhadap AI. Kami melakukan studi pemetaan sistematis dan menemukan 32 studi utama yang relevan. Temuan kami disusun menjadi dua aspek. Pertama, mensistematisasikan dan mengklasifikasikan penelitian yang ada berdasarkan jumlah makalah yang diterbitkan, tahun penerbitan, jenis penelitian, negara asal, metode penelitian, teori, dan kerangka kerja yang digunakan. Kedua, mengidentifikasi kesenjangan penelitian dan mengusulkan agenda penelitian yang akan datang. Sebagian besar artikel yang diterbitkan setelah tahun 2019 didominasi oleh penelitian eksploratif, empiris, dan deskriptif serta menggunakan metode kualitatif dan kuantitatif sebagai pendekatan dalam melakukan penelitian. Namun, penelitian mengenai kesiapan organisasi terhadap AI masih sering dilakukan di negara-negara maju. Penelitian ini memberikan kontribusi analisis tematik terhadap variabel penelitian, faktor adopsi AI, hasil implementasi AI, teori dan kerangka kerja, kesenjangan penelitian dalam literatur, dan agenda untuk penelitian masa depan. Dalam lingkup akademis perlu dilakukan mengenai kesiapan organisasi terhadap AI guna meningkatkan kejelasan konseptual, pengembangan teori, memahami manfaat dan nilai bagi bisnis, memahami faktor kontekstual, dan mengeksplorasi hasil secara kritis.
Kata kunci: organizational readiness; artificial intelligence; SMS; literature review; scopus

INTRODUCTION

Artificial Intelligence (AI), as an emerging technology, is widely discussed by scholars and professionals across industries, including automotive, transportation & logistics, pharma, agriculture and manufacturing (Collins et al., 2021). The impact of AI in transforming both businesses and societies is comparable to that of the internet and world wide web, and latter led to the emergence of ecommerce, consume-centric practices, sharing economy and gig economy (Malik et al., 2020). International Data Corporation has predicted that the global spending

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on AI will increase from $85.3 billion in 2021 to more than $204 billion in 2025, making the compound annual growth rate 2021-2025 to be 24.5%. According to the predictions made by the World Economic Forum, adoption of AI will make 75 million jobs redundant and create 133 million new ones worldwide by 2022 (Cann, 2018).

The COVID-19 pandemic has accelerated the adoption of AI technologies in businesses. The pandemic forced companies to adapt to online shopping, leading to increased reliance on AI for decision-making and operational efficiency. However, there are still challenges related to understanding AI implementation and addressing ethical and privacy concerns (Castillo & Taherdoost, 2023). Over 90% of productive organizations are considering enterprise-level AI adoption, and 37% have already implemented AI (ThiDang & MinhNguyen, 2022). AI is used for tasks such as optimizing inventory levels, intelligent fraud management, and personalized product recommendations, which enhance business efficiency and customer satisfaction (ThiDang & MinhNguyen, 2022).

The emergence of AI-based systems in the business organisations will significantly transform work force demographics, nature and meaningfulness of jobs, employer-employee relationship, relationship between people and technology, customer experience, and competitive advantage within a dynamic market environment (Connelly et al., 2021). The existing literature has claimed and outlined several benefits of AI adoption which includes, enhancing business productivity by optimising business operations and resources (Faulds & Raju, 2021), business model transformation/re-engineering (Duan et al., 2019), decision-making through predictive intelligence (Paschen et al., 2020), reducing employee costs and enhancing employee experience, job satisfaction and customer service (Paris & Washington, 2018). This has led to increasing uptake of AI-enabled solutions in HRM sub-functional domains such as talent acquisition, video interviews, employee training and development (Maity, 2019), performance evaluation, talent prediction (Upadhyay & Khandelwal, 2018) and employee engagement (Bankins & Formosa, 2019). In this context, recent reviews have outlined the role of AI to facilitate HR analytics (Margherita, 2022), and its potential impact on HRM processes and practices (Vrontis et al., 2021).

Academic studies on organizational readiness on AI are becoming more prevalent. Research indicates that large enterprises generally exhibit a more supportive organizational culture for AI integration compared to smaller firms. This is attributed to their greater capacity to foster innovation and experimentation, which are critical for successful AI adoption (Rožman, 2023). The organizational culture plays a pivotal role in determining how receptive an organization is to new technologies, including AI, as it influences the willingness to embrace change and invest in new capabilities (Kar et al., 2021).

Moreover, the complexity of AI technologies necessitates a thorough understanding of organizational readiness factors. Jöhnk et al. emphasize that AI adoption is distinct from other digital technologies due to its implementation complexity and the knowledge barriers it presents (Jöhnk et al., 2020). Organizations must conduct a readiness assessment to align their current capabilities with the intended AI applications. This alignment is essential for ensuring that the adoption process is not only effective but also sustainable in the long term (Noordt & Misuraca, 2020). The interplay between organizational culture and readiness is further supported by findings that highlight the importance of leadership and change capability in facilitating AI adoption (Kurup & Gupta, 2022).

In addition to cultural and structural factors, the role of employee engagement cannot be overstated. Dabbous et al. argue that successful AI adoption hinges on employees' acceptance and effective use of AI technologies (Dabbous et al., 2021). This necessitates a focus on individual and social factors that influence technology adoption within organizations. Furthermore, ethical considerations and the need for continuous learning are critical for fostering an environment conducive to AI integration (Shukla, 2023). The presence of supportive leadership and a culture that encourages collaboration and innovation are vital for overcoming resistance to AI adoption (Campion et al., 2020).

Barriers to AI adoption also merit attention. Common challenges include data sharing resistance, ethical concerns, and the potential for workforce displacement, which can hinder the adoption process (Booyse, 2023; Badi et al., 2021). Organizations must navigate these barriers by fostering an open culture that promotes data sharing and addresses ethical implications proactively. Additionally, the integration of AI into existing workflows requires careful planning and a clear understanding of the potential impacts on organizational dynamics (Paul et al., 2020).

However, to the best of our knowledge, there are no systematic literature reviews (SLRs) or systematic mapping studies (SMSs) regarding this topic. Some SLRs have been published in related areas. For example, Frangos (2022) review about required leadership capabilities and organizational imperatives (beyond technology) for AI readiness and adoption. Another research from Akbarighatar (2022) drawing from the literature review provides a matrix for AI maturity from a sociotechnical perspective and a conceptual maturity model with two main dimensions (covering both instrumental AI capabilities and capabilities for responsible AI). More examples from Jada & Mayayise (2024) who conduct a systematic literature review (SLR) to assess the impact of AI-based technologies on organisational cyber security and determine their effectiveness compared to traditional cyber security approaches.

Enhancing comprehension of the motivations, practical consequences, and issues posed by this emerging phenomenon may be achieved through an agile HRM mapping research. Unlike systematic literature reviews (SLRs), which summarize research findings for a specific research issue that has been the focus of several studies, mapping studies are meta-studies that map out research activity in a particular area (Kitchenham, 2004; Petersen et al., 2015). SMSs are often conducted in fields with relatively low levels of research activity. To provide insights into certain study domains, mapping studies answers issues such as what kind of studies have been conducted and when and where they were published. It also classifies and systematizes current research contributions (Petticrew & Roberts, 2008). SMSs are thorough reviews that describe a topic, summarize findings, explain how theory is used, point out research gaps, and emphasize areas that need additional investigation. They help to build specific and new study topics (Petersen et al., 2015).

Most of the innovation in how organizations utilize AI occurs in the real world, but in order to create deep understandings, models, and theories that synthesize and clarify crucial aspects of practice, academic research is required. An SMS into organizational readiness for AI is timely, even though SLRs have been used to study comparable phenomena. This is because the topic is being discussed frequently in practice and the body of research on it is expanding. In addition to identifying potential future research and practice development topics, this study will assist in educating scholars and practitioners on the state of the art now. This study makes two contributions. First, to systematise and classify existing research in terms of number of papers published, year of publication, type of the research, country of origin, research methods, theories, and models used. Second, to identify research gaps and propose a research agenda. To guide this research there are five research questions:

- RQ 1. How many papers have been published, and when were they published?
- RQ 2. What research methods have been used?
- RQ 3. How are papers geographically distributed?
- RQ 4. What research topics have been investigated?
- RQ 5. What underlying theories and models are used and what new frameworks are developed?

The novelty of the research lies in its systematic mapping study (SMS) approach to examining organizational readiness for Artificial Intelligence (AI). While there have been studies on AI's adoption across various sectors, this research fills a critical gap by providing a comprehensive review specifically focused on how organizations prepare for AI implementation. Unlike existing systematic literature reviews (SLRs) that summarize findings on AI adoption in related areas, this study distinguishes itself by classifying and systematizing research into organizational readiness, categorizing it by research methods, geographic distribution, and theoretical frameworks. The research also identifies the gaps in literature and suggests a structured research agenda for future exploration.

Moreover, this study’s emphasis on organizational readiness for AI in developing countries highlights its unique contribution. Previous studies have predominantly focused on AI adoption in developed nations. By shedding light on the underexplored areas such as the barriers and drivers specific to organizational AI readiness in a global context, this research contributes not only to the academic community but also provides practical insights for organizations looking to adopt AI, especially in sectors where AI readiness is still developing.

METHOD

This study used the systematic mapping study (SMS) approach to gather secondary data. This SMS methodology is adapted from the systematic literature review (SLR) approach (Tribis et al., 2018). The SMS method's objective is to provide an account of earlier research endeavours.

The procedure of searching for data needs to be done as precisely as feasible. By choosing the appropriate search phrase, exclusion-inclusion criteria, and mapping data source, this accuracy is demonstrated (Tahir et al., 2021). Because the Scopus database indexes the top journals with the most current papers, researchers utilized it to gather data (Aghaei Chadegani et al., 2013). Furthermore, according to Franceschini et al (2016), Scopus is the largest abstract and citation database, handling 1.4 billion citations and 16 million author profiles. It also offers more accurate data. The search terms used were 'Artificial Intelligence' AND 'Organizational Readiness'." To filter out the pertinent publications, the researcher then establishes the inclusion and exclusion criteria (Marew et al., 2007). Table 1 displays the inclusion and exclusion criteria that the author developed.

Table 1. Inclusion And Exclusion Criteria

No	Inclusion	Exclusion
1	English	Other than English
2	Only journal and conference proceeding	Other than journal and conference proceeding
3	Research that discusses on organizational readiness for AI	Research that not discusses on organizational readiness for AI

Source: Researcher, 2024

In this study, the process of analyzing and classifying articles was in accordance with predetermined criteria in table 1, the researchers developed a classification scheme (Marew et al. 2007). The classification scheme process is clearer as can be seen in Figure 1.

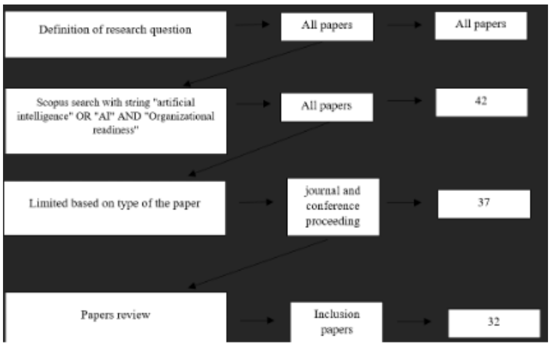

Figure 1. Stages of the Research Tracing Process

Source: Researcher, 2024

RESULTS AND DISCUSSION

An analysis of research trends shows how scholarly interest in organizational readiness for Artificial Intelligence has changed over nearly four decades, from 1985 to 2024 (Figure 2). The timeline starts in 1987, when there was only one publication that signalled the beginning of scholarly attention to organizational readiness. For the following three decades, the interest remained stagnant, as shown by a flat line that continued through 2019 and showed no additional publications during this long period. In 2019, a resurgence began with the publication of another article, which replicated the one from 1987. From this point on, however, there is a notable increase in research activity that is evident. In 2020, the number of articles increases to four, demonstrating a newly discovered and quickly growing body of work.

Research Trend

By 2021, there were five publications, continuing this growing trend. The trend peaks in 2023, when there are 10 published publications, a significant increase, indicating the pinnacle of intellectual activity. It's interesting to note that in 2024, the trend marginally declines with four publications, indicating either a temporary fall in research outputs or a plateau. After a protracted period of dormancy, organizational readiness research saw an explosive development phase starting in the late 2010s, indicating a dramatic shift in academic and maybe practical interest in comprehending and implementing organizational preparedness.

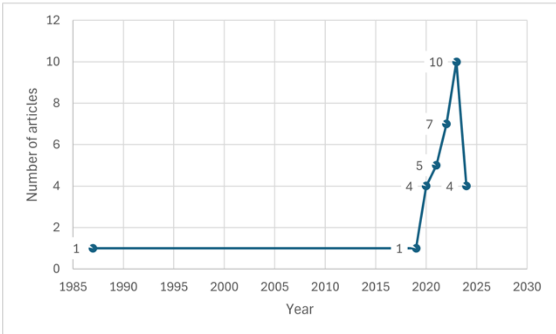

Figure 2. Research Trend

Source: Researcher, 2024

Several techniques are used in the Research of Organizational Readiness for AI to study how firms use and prepare for Artificial Intelligence (AI). The information displays how research efforts are split up into six different groups (Figure 3). With just two publications, the first conceptual research category has the fewest publications overall. In this respect, conceptual research entails creating hypotheses or models that are especially targeted at AI preparedness without waiting for instant empirical confirmation. The second type of study is cross-sectional studies, which are covered by four articles. In cross-sectional studies, data from a population or a representative subset is analysed through observational research at a particular point in time to determine the level of AI preparedness. Third, a thorough description of the existing organizational preparedness for AI is given in seven pieces of descriptive study. This research provides in-depth insights without concentrating on causation.

Fourth, empirical study. Additionally, empirical research supports a deeper knowledge of organizational AI preparedness by gathering and analysing data to test hypotheses and develop conclusions based on evidence, as demonstrated by the seven publications. The fifth category, exploratory research, has the most articles (9), demonstrating a keen interest in delving into the unexplored realm of AI preparation in enterprises and gaining fresh perspectives. The purpose of exploratory research is to uncover important topics for further study and to provide hypotheses. The sixth is the literature review A thorough examination of the present state of knowledge and the identification of gaps in the literature are provided by the three papers that make up the literature review, which summarizes the results of previous research on AI preparedness.

Research Type

The most common method is exploratory research, which reflects a strong desire to learn more and comprehend the nuances of organizational AI preparedness. Though fewer in number, conceptual and literature reviews provide crucial theoretical and integrative insights to the subject, while descriptive and empirical investigations also play a key role, providing thorough documentation and conclusions based on data.

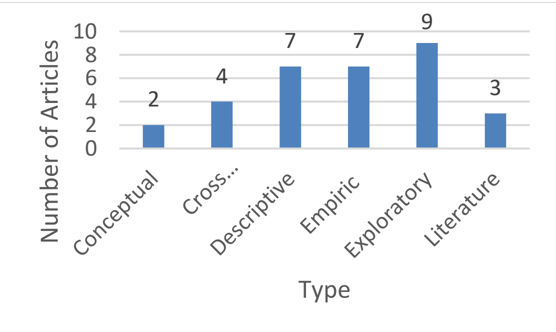

Figure 3. Research Type

Source: Researcher, 2024

The three types of quantitative, qualitative, and mixed methodologies research approaches used to examine organizational readiness for AI are represented in figure 4. With 50% of the studies, quantitative research is the most common type of study. To assess AI preparedness, this method probably concentrates on numerical data and statistical analysis, yielding unbiased and broadly applicable results. Examples include structural equation modelling (SEM) and partial least squares (PLS), which are used to assess the extent of AI integration.

Research Approach

Qualitative research constitutes 47% of the studies, indicating a nearly equal emphasis on understanding the human and contextual factors influencing AI readiness. This approach involves in-depth methods such as semi-structured interviews, single case studies and observation, which allow for a deeper exploration of organizational culture, employee attitudes, and the nuanced challenges and opportunities associated with AI adoption. The qualitative insights complement the quantitative data, offering a richer, more comprehensive view of AI readiness.

Despite being the lowest category (3%), mixed methods research exemplifies an integrated strategy that integrates both quantitative and qualitative methodologies. By combining the best features of both techniques, this methodology offers a comprehensive picture of an organization's AI preparedness. Researchers may provide a more robust and comprehensive study by combining qualitative insights with quantitative data through the use of mixed methods. The sparse application of mixed techniques may point to a developing pattern or highlight how difficult it is to combine these two research paradigms.

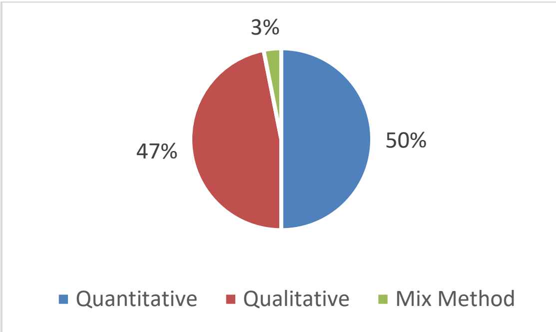

Figure 4. Research Approach

Source: Researcher, 2024

This part summary of the research sites and sectors concentrating on organizational readiness for AI. Interestingly, the healthcare sector is mentioned frequently in a variety of locations, including the USA, Canada, Finland, Spain, the United Arab Emirates, and the United Kingdom. This demonstrates how AI is being recognized on a worldwide scale for its ability to transform healthcare systems, improve patient care, and increase operational efficiency. This trend is highlighted in particular by the UAE, Canada, and Italy, which show a significant investment in incorporating AI into healthcare infrastructure.

The chart also illustrates a wide number of businesses outside of healthcare, demonstrating the broad application of AI. While Saudi Arabia and India concentrate on manufacturing and production, highlighting AI's role in industrial transformation, Australia and Germany, for example, take a broader approach with research covering numerous industries. Specific industries where AI can lead to major breakthroughs include the construction and environment sector in Singapore, the transportation industry in Greece, and the retail industry in Jordan. This varied portrayal highlights AI's many effects and emphasizes its significance in a variety of societal and economic contexts.

Table 2. Research location

Country	Industry
Australia	Large enterprises
	Multi industry
	Healthcare
Canada	SMEs
	Healthcare
	Healthcare
Finland	Healthcare
France	Food and beverage
Germany	Multi industry
	Multi industry
	Multi industry
Greece	Transportation
India	Manufacturing and Production
Italy	SMEs
	Healthcare
Jordanian	Retailing
Malaysian	Government institution
Pakistan	Education Institution
Saudi Arabia	Manufacturing and Production
Singapore	Building and environment
Spain	Healthcare
UAE	Healthcare
	Healthcare
	Healthcare
United Kingdom	Healthcare
USA	Healthcare
Vietnam	Multi industry
Western Europe	Exhibition company
Worldwide	Telecommunication

Source: Researcher, 2024

The different theoretical frameworks and models applied in assessing organizational readiness for AI. The theories are divided into three main categories: Technological Theory, Organizational Theory, and Environmental Theory. Each category lists specific theories that provide insights into various facets of AI readiness in organizations.

Theories that concentrate on the technical features and prerequisites for AI adoption are included in the category of technological theory. These ideas stress the need of recognizing and utilizing digital tools, evaluating the relative benefits of artificial intelligence, and guaranteeing technological maturity The technology-organization-environment framework is the most framework model among other frameworks that has been used for organizational readiness for AI research with 11 articles for instance, research that conducted by wael AL-khatib (2023) and (Min & Kim, 2024). When assessing an organization's readiness for Artificial Intelligence (AI) and the advantages it expects from these technological breakthroughs, tools like the Technological Readiness Index and Technological Perceived advantages are essential (Hradecky et al., 2022).

Organizational theory looks at how an organization's internal dynamics affect how prepared it is for artificial intelligence. Many theories, including Digital Organizational Culture (Aliane et al., 2023), Competitive Advantage (COA) (Chatterjee et al., 2021), and Organizational Trust (Seethamraju, R. & Hecimovic, 2023), show in this area. These ideas look at how internal procedures, organizational culture, leadership, and structure affect an organization's capacity to accept and use AI technology. Organizational Competency (OCM) and Organizational Compatibility (OCO) guarantee that the workforce is competent and that organizational procedures are in line with AI deployment (Chatterjee et al., 2021), while Managerial Support and Leadership Support (LS) are essential for spearheading AI efforts (Frangos, 2022).

Organizational readiness for AI is influenced by external influences, which are examined by environmental theory. This covers notions such as government involvement (AlSheibani et al., 2020), competitive pressure (Phuoc, 2022), and client readiness (Seethamraju, R. & Hecimovic, 2023). These theories investigate the ways in which outside forces and support networks influence an organization's choice and capacity to embrace AI. For example, the significance of adjusting to external environmental circumstances and market dynamics is emphasized by Environmental Sustainability and Market Uncertainty. Vendor Partnership highlights how outside alliances and cooperation aid in the deployment of AI. When combined, these ideas offer a thorough framework for comprehending and improving organizational preparation for AI in many contexts (Phuoc, 2022).

Table 3. Research Theory and Framework

Categorize	Theory
Technological Theory	Artificial intelligence
	Artificial Intelligence readiness
	Artificial Intelligence for its operations (ai-ops)

Categorize	Theory
	Artificial Intelligence library services (ai-lsicf)
	Digital capabilities
	Digital transformation
	Digital awareness
	Digitalization
	Generative Artificial intelligence
	Relative advantages
	Technology acceptance model tam
	Technical complexity
	Technical compatibility
	Technological maturity
	Technological perceived benefits
	Technology readiness index
	Technology-organization-environment frameworks
	Benefits, organisational readiness and external pressure Frameworks
	Organizational readiness
	Organisational trust
	Competitive advantage (COA)
	Customer relationship management
	Digital organizational culture
	Enterprise architecture
	Leadership support (LS)
	Supply chain management
Organizational Theory	Organisational culture
	Organisational data quality,
	Organisational quality
	Organization size
	Organizational capabilities
	Organizational compatibility (OCO)
	Organizational competency (OCM)
	Organizational complexity (OCX)
	Organizational motivation
	Partner support (PSU)
	Top management support,
	Client readiness
	Competitive pressure
Environmental Theory	Environmental sustainability
	Government Involvement
	Market uncertainty
	Vendor partnership

Source: Researcher, 2024

We separated the organizational readiness study for AI into four areas to facilitate the mapping of research findings: correlation variables, factor AI adoption in organization Level, implementation and evaluation of AI adoption, lastly, theory and framework.

1. Correlation variables

There are 5 articles that study the relationship between variables in the context of organizational readiness for AI with different variable between them. One of these studies from wael AL-khatib (2023) showed that the adoption of generative Artificial Intelligence is not significant impacted by technological compatibility or competitive competitive pressures. Complexity was found to have a detrimental impact on the adoption of generative AI. However, the results also support generative AI's beneficial effects on both exploratory and exploitative innovation.

Moreover, a different study from Denicolai et al (2021) discovered a significant correlation between SMEs' worldwide success and their readiness for artificial intelligence. They also discover that sustainability and digitization are positively correlated, but that when a company expands internationally, they become rival development routes.

One of the results (Chatterjee et al., 2021) highlights that organizational competency, organizational complexity, competitive advantage support on perceived ease of use, were found to be significant in the context of digital manufacturing and production organizations except for organizational readiness, organizational compatibility and partner. The results further indicated that leadership support acts as a countable factor to moderate such an adoption.

Furthermore, Artificial Intelligence and digital capabilities have a positive impact on digital awareness, and digital awareness has a positive association with supply chain management (Aliane et al., 2023). The outcomes also exposed that digital awareness significantly mediates among artificial intelligence, digital capabilities and supply chain management and organizational readiness and digital organizational culture significantly moderate among digital awareness and supply chain management.

2. Factor AI Adoption in Organization Level

Based on the 32 articles analyzed, there are 11 articles that discuss the factors causing AI to be adopted by organizations. Top drivers founded by Shang et al (2023) include support from top management and leadership, organizational readiness, and the need for greater productivity and efficiency. Conversely, significant barriers identified are the high costs associated with AI implementation and maintenance, as well as a lack of top-down support and skilled employees trained in AI. On the other hand, Abuzaid et al (2022) have different thoughts, they conclude that four primary motivations for adopting AI are fostering practice change, promoting system-level change, emphasizing organizational readiness, and integrating AI technologies. Government support is also highlighted as a key enhancer for organizational and technological readiness, thus positively influencing AI adoption intentions.

Further findings emphasize that AI adoption readiness in various sectors is influenced by organizational and technological practices, financial resources, and external pressures such as Covid-19 (Hradecky et al., 2022). The study identifies factors like technical compatibility, managerial capability, and government involvement as significantly related to AI adoption. Interestingly, the size of an organization was not found to be statistically significant in influencing AI adoption (Phuoc, 2022) but from Hradecky et al (2022) found that organization size motivates the readiness of AI. Additionally, interesting research from Min & Kim (2024) highlights the comparative research between organizations intending to adopt AI (demander group) and those assisting in AI adoption (provider group), revealing that organizational factors are crucial for the demander group, while technological factors are more critical for the provider group.

3. Implementation and Evaluation of AI adoption on Organization Level

The results of research analyzing organizations that have implemented AI show that organizations still need a lot of improvement and some recommendation from the researchers This is supported by 11 research results on organizational readiness for AI. The first research was conducted in western Europe by (Hradecky et al., 2022) shows that The European exhibition industry is a slow adopter of AI. Moreover, most of Greece's operators of transportation have relatively low levels of maturity, according to survey results in the public transportation sector. It appears that the maturity index findings of the actors are unaffected by their operational location. Findings further demonstrated that most of the Greek operators under investigation do not make use of AI technology (Kopsacheilis et al., 2021). Additionally, in Pakistani University Libraries, the library and information sector of Pakistan is slow in adopting AI, which could have implications for its future competitiveness, despite the push for AI adoption by university librarians and administrators (Jan et al., 2024).

The same thing is also shown in the healthcare sector, the application of Artificial Intelligence (AI) in radiology practice was not well understood or appreciated. Organizations are starting to develop plans for using AI. For radiologists as well as radiographers, the biggest obstacle is finding suitable training programs. In order to close the knowledge gap, professional associations and educational institutions must work together to provide organized training programs for radiologists and radiographers (Abuzaid, Elshami, Tekin, et al., 2022). Unfortunately, this not happen in radiologists, mental health professionals also deal with same problem (Zhang et al., 2023) and nursing profession that need education and training to enable a seamless and safe integration of AI into nursing practice (Abuzaid, Elshami, & Fadden, 2022).

Fortunately, some researchers give their best suggestions to handle the lack of knowledge of AI adoption in organizations. Based on the analysis of industrial case studies and observation from Sandkuhl & Rittelmeyer (2022) shows that different kinds of AI applications require different prerequisites in an organizational IT landscape, some of which can be found in an enterprises architecture (EA) model, and some enterprises intend to use AI but are not prepared for it. The work investigates what information can be harvested from EA models to support requirements engineering and the evaluation of organizational readiness for AI planning and implementation.

Additionally, Kamath et al (2024) recommend the following for an AI mentoring program for the healthcare industry: (1) securing organizational commitment for each participant; (2) integrating structural support throughout the program; and (3) using a team-based mentorship strategy. Additionally, AI-enabled software is transforming the healthcare industry by lowering costs and increasing overall effectiveness. A policy for AI integration should be created to specify the primary duties and responsibilities of dentists, as well as the ethical and regularity standards. The policy is expected to enhance the level of contact and communication among suppliers, stockholders who are dentists, and the scientific community (Hamd et al., 2023) .

The following factors should be better taken into account as a crucial first step in ensuring the successful integration of AI, avoiding needless expenditures and expensive mistakes: (1) needs and added-value assessment; (2) workplace readiness: stakeholder acceptance and engagement; (3) technology-organization alignment assessment; and (4) business plan: financing and investments. In conclusion, decision-makers and proponents of technology ought to better tackle the complexities of Artificial Intelligence (AI) and comprehend the systemic issues that arise from implementing it in healthcare systems and organizations (Alami et al., 2021).

4. Theory and Framework

Several researchers also put forward several new findings in the form of theories as a reference for future scientific research. The findings of Taherizadeh & Beaudry (2023) define the essential components of AI-driven digital transformation (AIDT) and provide a grounded theory that offers a comprehensive and nuanced picture of how the process works inside SMEs in Canada. The analysis shows the interaction of five fundamental dimensions of the AIDT process: evaluating transformation context, auditing organisational readiness, piloting the AI integration, scaling the implementation, and leading the transformation. 25 AI professionals were interviewed in-depth by Jöhnk et al (2021), who also triangulated the results with practitioner and scientific literature. The study found that there are five elements that contribute to AI readiness which are Strategic alignment, resources, knowledge, culture and data

To be employed in this context, the basic TOE framework—which has been applied to other technologies like cloud computing—needs to be reviewed and expanded. New and noteworthy considerations have surfaced, such as data availability, quality, and protection, as well as regulatory concerns stemming from the recently implemented General Data Protection Regulation (Pumplun et al., 2020).

CONCLUSION

This study investigates organizational readiness for Artificial Intelligence (AI) using a systematic mapping study (SMS) approach to analyze research trends, types, approaches, and frameworks from 1985 to 2024. It reveals a resurgence of interest in AI readiness post-2019, highlighting a diverse range of research methods including exploratory, empirical, and conceptual studies, with a notable emphasis on quantitative research. The analysis identifies key drivers and barriers to AI adoption, such as managerial support and high costs, respectively, and highlights sector-specific readiness levels, particularly in healthcare. The study underscores the necessity for tailored strategies to enhance AI adoption, emphasizing the importance of training, organizational commitment, and alignment of technological and organizational practices. Various theoretical frameworks, including but not limited to the TOE framework, can guide future research and implementation practices.

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