A Review of Determinants Influencing Artificial Intelligence Systems Adoption

Sultan Saif AL Maawali[1], Dr. Azlina binti Abdullah[2], Dr. Abbod ALtamami [3], Dr. Wan Noordiana Wan Hanafi[4]

1UNITEN–Putrajaya Campus, Jalan IKRAM-UNITEN, 43000 Kajang, Selangor, Malaysia; almawalisultan@gmail.com (I.A.A.B.).

2UNITEN–Putrajaya Campus, Jalan IKRAM-UNITEN, 43000 Kajang, Selangor, Malaysia; azlina@uniten.edu.my (N.Y.B.M.).

3UNITEN–Putrajaya Campus, Jalan IKRAM-UNITEN, 43000 Kajang, Selangor, Malaysia; abbod.naseb@uniten.edu.my (N.Y.B.M.).

4UNITEN–Putrajaya Campus, Jalan IKRAM-UNITEN, 43000 Kajang, Selangor, Malaysia; diana.hanafi@uniten.edu.my (N.Y.B.M.).

HOW TO CITE:

Sultan Saif AL Maawali, Azlina binti Abdullah, Abbod ALtamami, Wan Noordiana Wan Hanafi (2026). A Review of Determinants Influencing Artificial Intelligence Systems Adoption. International Journal of Special Education, 41(10s), 61-78

COPYRIGHT STATEMENT:

Copyright: © 2026 Authors.

Open access publication underthe terms and conditions of the Creative CommonsAttribution (CC BY) license (http://creativecommons.org/licenses/by/4.0/).

ABSTRACT:

This paper seeks to pinpoint and explain the elements that affect the adoption of AI at both the organisational and individual levels. By crafting a conceptual model, it enriches our comprehension of the fundamental individual, social, technological, organizational, and environmental influences and paves the way for future inquiries in this domain. This research has categorized the elements affecting AI system adoption into individual, social, organizational, environmental, and technological dimensions. Organizational factors were discovered to influence how employees respond to AI systems. Additional exploration is essential to discern how these factors shape employee perceptions, feelings, and actions regarding novel AI systems. These insights prompted the creation of a theory-based model that illustrates the connections between these elements, contesting the notion of independence among adoption influencers at both the organisational and individual levels. This investigation is among the pioneering efforts to amalgamate existing insights on the drivers of AI adoption, establishing a theoretical base for further studies in this burgeoning area. The adoption model constructed integrates vital factors from both organisational and individual perspectives, providing a comprehensive outlook on the interrelatedness of various AI adoption elements. This methodology questions the belief that factors at the organisational and individual levels function separately. Through this, information systems scholars and practitioners attain a richer understanding of AI uptake, deepening their awareness of its potential ramifications.

Keywords: Artificial intelligence, adoption, acceptance, Organizations , AI Adoption.

1. Introduction

Artificial intelligence (AI) technologies have revolutionized the commercial landscape, reshaping how businesses execute their functions and responsibilities (Tjebane et al., 2022). Companies are progressively integrating AI solutions due to the vast potential and advantages they offer (Oppioli et al., 2023). Numerous organizations have allocated resources and devoted time and finances to implement AI systems effectively. Nonetheless, the journey to embracing AI remains fraught with obstacles, and the rate of AI project failures is alarmingly high (Makarius et al., 2020). Data from 2020 indicated that 70% of AI initiatives failed to deliver the expected advantages, prompting many firms to abandon their AI endeavors. Furthermore, the rate of AI project failures surged between 2019 and 2020, with cancellations soaring from 20% to 40% (Makarius et al., 2020).

In order to address this phenomenon effectively and enhance the success of AI adoption initiatives, this research undertakes several fundamental steps by;

- Structuring the existing literature regarding the factors influencing AI adoption at both the organizational and individual levels,
- Proposing a holistic model that elucidates the interrelations among various categories of determinants and their influence on the decision-making process for AI adoption at both the organizational and individual levels, and
- Pinpointing deficiencies in the current literature and offering recommendations for future scholarly inquiry.

In order to effectively adopt and implement artificial intelligence systems and derive advantages from investments in AI, it is imperative for managers to comprehend the facilitators and impediments associated with AI adoption. From a pragmatic standpoint, this investigation furnishes managers with an extensive insight into the factors influencing AI adoption that warrant consideration prior to initiating such endeavors or allocating resources towards them. Consequently, the factors influencing AI adoption and implementation have garnered heightened scholarly attention in recent years (Tjebane et al., 2022; Na et al., 2022). Prior research has explored the determinants of AI adoption at both the organizational and individual employee levels. While earlier investigations have employed an array of theoretical frameworks and models, including the "Technology-Organisation-Environment" (TOE) framework, "Diffusion of Innovations" (DOI), "Unified Theory of Acceptance and Use of Technology" (UTAUT), and "Technology Acceptance Model" (TAM) to elucidate the determinants of AI adoption (Dabbous et al., 2022; Kinkel et al., 2022; Getson and Nejat, 2022), there exists a notable absence of any review articles that provide a holistic overview of these determinants.

Prior investigative studies have scrutinized the implementation of artificial intelligence (AI)-oriented systems. For example, Oppioli et al. (2023) examined the ramifications of AI in management decision-making, emphasizing its assimilation across diverse business operations, which significantly affects the comprehension of human behavioral patterns. Pietronudo et al. (2022) assessed the impact of AI on innovative management as a component of the decision-making paradigm. Pramod (2022) explored the impediments related to the incorporation of robotic process automation (RPA) systems, whereas Pradhananga et al. (2021) concentrated on the adoption challenges pertaining to robotics within the construction sector, and Regona et al. (2022) investigated AI integration within the construction industry. Ghandour (2021) and Wang et al. (2021) conducted a comprehensive review of the literature concerning AI adoption in the banking sector and within the framework of Chinese smart cities, respectively. Additionally, Yu et al. (2022) performed a review study analyzing the antecedents and ramifications of AI adoption in organizations through the lens of socio-technical system theory.

Bawack et al. (2022) executed a bibliometric investigation to examine and synthesize the extant literature pertaining to artificial intelligence

in the e-commerce domain, aiming to ascertain the present status of this research area. Secinaro et al. (2021) performed a bibliometric examination of the applications of artificial intelligence within the healthcare sector, with the objective of identifying prominent journals, notable authors, and seminal works, while also elucidating significant themes and evolving trends in this field of inquiry. Di Vaio et al. (2020) presented an extensive analysis of the ways in which artificial intelligence can facilitate the advancement of sustainable business models that are congruent with the Sustainable Development Goals (SDGs).

Additional information pertaining to these review studies is delineated in Table I. The concluding row of this table encapsulates the aims, methodology, and results of this research, underscoring its significance in addressing deficiencies within the existing literature.

Table I Summary of review studies .

Author	objectives	methodology	Databases	Discoveries
Oppioli et al. (2023)	Identify the AI system in management decisions.	• PRISMA methodology to collect and screen the papers. • Bibliometric analysis usin g Bibliometrix package and R studio.	Scopus.	The research examines the extensive integration of Artificial Intelligence (AI) within management processes, highlighting its critical role in automating supply chains, enhancing customer relations, and assisting in executive decision-making. The study points out that AI optimizes these processes by analyzing behavioral trends and aligning with established frameworks like the Technology Acceptance Model. Moreover, it underscores that the successful adoption of AI is heavily dependent on addressing ethical concerns, particularly those involving data privacy and the secure management of personal records
Pietronudo et al. (2022)	Analyse the literature on AI's influence on decision-making in innovation management.	Bibliometric and thematic analysis.	Scopus	The research indicated that although artificial intelligence is anticipated to enhance and facilitate the management of innovation, it does not consistently optimize decision-making processes; instead, it functions as a multifaceted instrument that exerts both intended and unintended rationalizing effects. Four

				primary impacts of artificial intelligence were delineated: the augmentation of rationality and creativity, the revitalization of organizational frameworks conducive to innovation, and the emergence of new challenges. This underscores the intricate role of artificial intelligence in navigating the tumultuous landscape of innovation management.
Pramod (2022)	Identify the applications, benefits, and challenges of robotic process automation systems across different industries. • Identify the industries that have adopted robotic process automation systems.	PRISMA methodology to collect and screen the papers.	Scopus, Web of Science, and Google scholar.	The research elucidated the various applications and advantages of Robotic Process Automation (RPA) systems across diverse sectors, revealing that these automation technologies are extensively implemented within the banking sector while exhibiting moderate utilization in the healthcare and manufacturing sectors.
Pradhananga et al. (2021)	dentify and explore the adoption barriers of robotics in the US construction industry.	Scientometric review of the literature. • Survey to validate the identified barriers	Scopus, ASCE, and ScienceDirect library.	The research delineated many of distinct obstacles to the implementation of robotic technologies within the construction sector of the United States. The primary determinants adversely affecting the integration of robotic innovations in the construction domain are highlighted.
Regona et al. (2022)	• Identify prominent AI technologies in the construction industry. • Understand the applications of AI technologies across	PRISMA methodology to collect and screen the papers.	copus, Web of Science, ScienceDirect, Directory of Open Access journals, and Wiley Online Library.	The research elucidated that proficient data management and the integration of the Internet of Things (IoT) are imperative for the successful adoption of artificial intelligence (AI) within the construction sector. Principal

	construction stages. • Determine the opportunities and challenges of AI in the construction industry.			opportunities encompass the minimization of redundant tasks, the optimization of processes, and the augmentation of planning precision. The challenges encountered include the necessity for continuous algorithmic training, difficulties in data acquisition, and the need for compatibility with pre-existing processes. Organizations must modify their structural frameworks and allocate resources towards research and development (R&D). Prospective trends indicate a rise in affordability, an expansion in the utilization of AI, enhanced adaptability, and improved integration within the industry.
Ghandour (2021)	Identify, assess, and synthesise the current literature on opportunities and challenges related to the use of Artificial Intelligence (AI) in the banking sector.	papers were reviewed, summarised, and synthesised	copus, Google Scholar, ProQuest, EBSCOhost, and Springer.	Personalized services, smart wallets, improved decision-making, customer satisfaction, process automation, and increased security are just a few of the advantages and potential that the study found for AI in banking. However, industry stakeholders must pay strategic attention to issues including employment loss, privacy concerns, decreased innovation, limited implementation, digital divide, problems with data quality, and loss of human touch.
Wang et al. (2021)	Identify and analyse the challenges influencing the adoption of AI and the Internet of Things (IoT)	PRISMA methodology to collect and screen the papers. • DEMATEL technique.	Major English and Chinese academic search engines, including Web of Science, Engineering Village, Scopus, Google Scholar,	Ten major obstacles to implementing AI and IoT in Chinese smart cities were identified by the study: a lack of infrastructure, a lack of funding, cybersecurity and

	in the context of Chinese smart cities.		CNKI, and Wanfang Data.	data risks, smart waste management, a shortage of professionals, managing energy demands, transportation, environmental risks, public health and education, and a lack of trust in AI and IoT. The study, which used the DEMATEL approach, discovered that the main factors impeding the adoption of AI and IoT in Chinese smart cities are a lack of infrastructure, a lack of funding, cybersecurity threats, and a lack of trust.
Yu et al. (2022)	Synthesise existing literature on AI adoption. • Identify and develop research propositions on the antecedents and consequences of AI usage. • Categorise the consequences of AI adoption.	Articles were retrieved by searching several databases.	Business Source Complete (EBSCO), ScienceDirect, Emerald, Elsevier ProQuest, and Google scholar.	In order to determine the causes and effects of AI adoption, the study created a conceptual framework based on socio-technical system theory. The organizational structure subsystem, technological subsystem, personnel subsystem, and environmental factors are the antecedents. Adoption and use of AI can have effects on individuals, organizations, and employment.
Bawack et al. (2022)	Analyse and synthesise existing research on AI in e-commerce. • Determine the current state of the field of information systems. • Propose future research directions within the Information Systems discipline.	Bibliometric analysis	Web of Science	The study included a thorough summary of AI research in e-commerce, showing that recommender systems, sentiment analysis, trust, personalization, and optimization are the main areas of interest. With notable papers in computer science, artificial intelligence, business, and management journals, it names China and the United States as major contributors to this field of study.

Secinaro et al. (2021)	Investigate and analyse the AI research in healthcare.	PRISMA methodology to collect and screen the papers. • Bibliometric analysis.	Scopus	The study recognized prominent authors and highly cited publications that direct the use of AI in nurse rostering and other medical applications, as well as the top journals that serve as key publication venues for AI in healthcare research. Furthermore, co-occurring terms highlight AI's contribution to improving diagnostic precision, effectively managing health services, and reconstructing patient histories from data, demonstrating its significant influence on clinical decision-making and health services administration.
Di Vaio et al. (2020)	Identify the role of AI in the construction of sustainable business models.	Bibliometric analysis.	Web of Science and Google Scholar	The study gave a thorough summary of how AI can help create sustainable business models that are in line with the Sustainable Development Goals (SDGs), pointing out gaps in the literature and the necessity of knowledge management systems to help businesses adapt their cultures in order to meet these objectives. It highlights how AI may improve sustainability by
This study	• Identify and explain the factors affecting AI adoption in organisations. • Develop a conceptual model to guide future research on this topic.	PRISMA methodology to collect and screen the papers. • Content analysis.	Scopus	The adoption of AI systems in businesses was found to be significantly influenced by individual, social, organizational, technological, and environmental aspects. In order to better understand and improve AI adoption techniques, it suggests a theory-based model that illustrates the interconnected

				relationships among these aspects.

Source(s): Authors own work

This investigation seeks to address this deficiency by conducting a comprehensive review of scholarly articles that examine the variables affecting the adoption of artificial intelligence. The aims of this systematic literature review are:

(1) to elucidate the factors that determine AI adoption at both the organizational and individual employee levels
(2) to formulate a conceptual framework that clarifies the interrelationships among the determinants of AI adoption.
(3) to integrate the existing literature on AI adoption and offer guidance for subsequent research endeavor.

2. Literature review

The Technology Acceptance Model (Davis, 1989) has been extensively utilized and refined in contemporary scholarly research, encompassing a myriad of dimensions to elucidate the intricate dynamics that govern the assimilation of innovative technologies and products. Wu and Chen (2017) posited that the framework of TAM remains constrained in its ability to encapsulate consumer attitudes and beliefs prior to or subsequent to acceptance. Yoon and Cho (2016) further contended that the TAM inadequately addresses the complexities inherent in multifaceted contexts, primarily due to the absence of critical constructs essential for comprehending user intentions towards the adoption of avant-garde technology. According to Venkatesh et al. (2012), the TAM was originally conceptualized for organizational environments; however, there has been a persistent demand for its extension to encompass broader applications.

To address the previously mentioned limitations and enhance its explanatory capacity, the Unified Theory of Acceptance and Use of Technology (UTAUT), as formulated by Venkatesh et al. (2003), amalgamated a variety of theoretical concepts and constructs. Dang et al. (2018) assert that the formulation of this theoretical framework entailed a meticulous analysis and integration of components derived from eight disparate models that prior scholarly investigations had utilized to elucidate the manner in which individuals engage with technology. The UTAUT model is fundamentally focused on elucidating the mechanisms that govern an individual's propensity to engage with a technological system and its resultant behavioral outcomes. As noted by Chang et al. (2013), the model delineates four pivotal factors that significantly influence the adoption of information systems: facilitating conditions (FC), performance expectancy (PE), social influence (SI), and effort expectancy (EE).

The integration of technology across various contexts has been thoroughly examined through the lens of the UTAUT model. The research conducted by Zhang et al. (2022) regarding the determinants influencing the acceptance of electric vehicles (EVs) in China was grounded in the UTAUT theoretical framework. Jain et al. (2022) explored the factors that impact the adoption of electric vehicles in India, utilizing the theoretical foundations of the UTAUT model. The UTAUT framework was employed by Chaveesuk et al. (2023) to scrutinize consumer acceptance patterns for autonomous vehicles in Thailand. Lastly, Abbasi et al. (2021) analyzed the motivations driving Malaysian users' acceptance of electric vehicles through the application of the UTAUT theory.

According to Venkatesh et al. (2012), prior research posits that the UTAUT model is predominantly constructed to evaluate consumers' preliminary acceptance of innovative information technology predicated upon their technological expectations. As articulated by Goodhue and Thompson (1995), the Task-Technology Fit (TTF) framework asserts that users are unable to effectively engage with a system or technology if it fails to align with their distinct operational requirements.

Consequently, the mere emphasis on behavioral and social determinants is inadequate; to accurately predict the assimilation of new technology, scholars must incorporate both task-specific and technological necessity dimensions, as articulated by Wu and Chen (2017). Prior investigations into technology adoption indicate that the integration of TTF and UTAUT yields superior outcomes compared to the application of either framework in isolation, as observed by Shahbaz et al. (2021). For example, Kim et al. (2022) adeptly employed UTAUT and TTF to investigate consumer intentions regarding omnichannel experiences within the automotive sector.

Furthermore, this amalgamation of UTAUT and TTF has been effectively applied across various sectors, including banking (Tarhini et al., 2016; Zhou et al., 2010), education (Wang et al., 2022; Wan et al., 2022), healthcare (Kang et al., 2022; Gu et al., 2021), and tourism (Sun and Guo, 2022).

The scholarly discourse encompassing the Technology Acceptance Model (TAM) and the Unified Theory of Acceptance and Use of Technology (UTAUT), with an emphasis on technological adoption across diverse domains.

Healthcare is distinguished as the economic sector that has undergone the most extensive investigation utilizing both UTAUT and TTF frameworks, thereby illuminating the pivotal role that technology adoption plays in the enhancement of healthcare systems. Conversely, the public, construction, and manufacturing sectors remain relatively unexplored, signaling an imperative for further research to deepen our understanding of technology adoption within these industries through the lenses of UTAUT and TTF. Collectively, these investigations underscore the importance of integrating UTAUT and TTF in order to comprehensively assess user intentions and acceptance of a variety of technologies across multiple industries and contexts, ultimately contributing to an enriched understanding of technology adoption trends and facilitating its effective implementation.

2.1. Results and findings

Previous investigations have employed firm-centric theories and frameworks, including the Technology-Organization-Environment (TOE) framework, institutional theory, and resource-based theory, to elucidate the determinants influencing technology adoption at the organizational level, while theories focused on individual behavior, such as the Technology Acceptance Model (TAM), the Unified Theory of Acceptance and Use of Technology (UTAUT), have been utilized to elucidate the factors motivating technology adoption at the individual level. The prevailing assumption posits that the factors pertaining to organizational and individual levels operate independently of one another. In this comprehensive review, we critically interrogate this assumption to investigate whether the determinants of technology adoption at both the individual and organizational levels are interrelated, thereby facilitating the development of a more integrative adoption model. We systematically categorized the determinants into four overarching dimensions: individual, social, technological, and organizational.

3.1. Individual and social factors

Individual and societal determinants may be classified into factors associated with perception and affect, personal attributes, and social influences.

3.1.1. Individual perceptions and feelings

Perceived utility, perceived usability, perceived hazards, perceived reliability, perceived security, concerns about job displacement, reluctance to interact with AI systems, and anxiety related to their use are among the factors related to perception and emotional reactions and their consequences for the adoption of AI as described in the scholarly discourse.

Although process and task automation is generally seen as a major organizational benefit (Yu et al., 2022), it may cause employees to worry about being replaced by AI technologies and possibly losing their jobs (Al Badi et al., 2022).

Fear of losing one's work could make people reluctant to adopt and use the new system (Pramod, 2022). AI-powered systems have the potential to drastically change how workers carry out their responsibilities and the inherent character of those activities. This could cause anxiety (Cao et al., 2021) and prevent workers from embracing such advancements (Sibbald et al., 2022).

3.1.2. Personal characteristics

The literature highlights a number of personal traits that affect the adoption of AI systems at the individual level, including self-efficacy, personal inventiveness, willingness to learn and share knowledge, beliefs, development concerns, system usage experience, ICT/AI knowledge, and ICT competence. Employee intentions to adopt and use AI systems may be influenced by worries about their capacity to learn or apply them (self-efficacy) (Yu et al., 2022). Workers who are more likely to pick up new skills might be more inclined to use AI systems (Pizam et al., 2022).

Conversely, employees' adoption of AI systems is adversely affected by a lack of expertise in digital technologies and AI systems (Nam et al., 2021). Adoption of AI is positively impacted by the desire to learn and share information (Choi et al., 2022). According to Dabbous et al. (2022), employees' intentions to adopt and use the AI system may also be influenced by their impressions of how using it reflects their views and ideas. For some workers, gaining experience and developing personally are crucial. If these workers believe AI systems will impede their personal growth, they might be less inclined to adopt them (Ghandour, 2021).

3.1.3. Social factors

According to Vichitkraivin and Naenna (2021), social factors are the effects of social influence and other people's opinions on a user's beliefs, sentiments, and intention to utilize a technology. Adoption and use of AI systems are influenced by social factors such as perceptions of the social surroundings of AI systems, perceptions of the social surroundings of the individual (image), and impact on the community. Organizations and employees may be influenced to embrace AI systems by the opinions of social groups (Pramod, 2022).

Employees' intentions to adopt the new system are positively influenced by their personal relationships, which facilitate good communication and debates about it (Tyson and Sauers, 2021). Employee behavior toward the use of AI systems is influenced by supervisors' and coworkers' thoughts and perceptions of the systems (subjective norms or social influence) (Rantanen et al., 2018). Their decision to use the system is also influenced by what their coworkers think of the employees who use it (Bröhl et al., 2019).

3.2. Organisational factors

Organizational aspects include things like leadership and management, competences, capabilities, and resource availability that have an impact on the adoption of technology (Phuoc, 2022). AI has an impact on organizations on both an organizational and individual level. The elements that influence a firm's decision to adopt a technology are referred to as firm-level influencing factors. Employee adoption and use of technology are influenced by elements at the individual level.

3.2.1. influencing organisational factors

Organizational readiness (Agarwal, 2022), AI governance systems (Bedué and Fritzsche, 2022), financial readiness (Bademosi and Issa, 2021), firm size (Golightly et al., 2022), technical readiness (Grover et al., 2022), and reliability and accuracy concerns (Al Badi et al., 2022) are the firm-level organizational factors influencing the adoption of AI. Organisational readiness refers to the degree to which an organisation is prepared to adopt a new system, and involves its structure, resources, processes, organisational infrastructure, management readiness, and strategy (Agarwal, 2022; Pramod, 2022).

Organizational business procedures and strategic objectives are significantly altered by the use of

AI technologies (Yu et al., 2022). Therefore, establishing a successful AI adoption plan aids organizations in making efficient use of their time, resources, and capabilities, which leads to time savings, decreased risks, improved performance, and perceived benefits of AI (Tjebane et al., 2022). Establishing expectations and priorities is crucial for organizations because it makes it easier for workers at all levels to collaborate, coordinate, and communicate clearly. As a result, it is imperative to make sure that priorities and expectations are clearly established.

Another crucial factor in the adoption of AI systems is the organizational governance structure (Pramod, 2022). To teach AI systems to produce correct results and fully utilize their potential, data exchange is necessary (Campion et al., 2022). In order to promote the adoption of AI, organizations must design and implement a governance structure, improve existing ones (Pramod, 2022), establish standards and a framework for sharing and using data (Regona et al., 2022), and create quality assurance procedures (Pramod, 2022).

3.2.2. Organisational factors influencing both firm- and individual-level adoption

Clarity of roles and responsibilities (Baumgartner et al., 2022), innovation culture (Neumann et al., 2022), resistance to change (Priya et al., 2022), collaboration and communication culture (Tjebane et al., 2022), availability of experts and skilled resources (Agarwal, 2022), task complexity (Kinkel et al., 2022), effective operations (Campion et al., 2022), managerial capabilities (Phuoc, 2022), top management support (Grover et al., 2022), and technology implementation experience (Bademosi and Issa, 2021).

AI implementation necessitates changing employee roles and providing explicit tasks because it alters organizational processes. Employee involvement and engagement in the adoption and implementation process are increased when roles are clearly defined (Mogaji and Nguyen, 2022). Adoption of new concepts and procedures is facilitated by an organization's innovative culture. According to Delgado et al. (2019), a strong organizational innovation culture encourages workers to embrace modifications in the way tasks are carried out utilizing the new technology. Adoption of new technologies also requires cooperation and a communication culture. Successful implementation can be facilitated by personnel from various departments working together effectively to share their knowledge and experiences and improve comprehension of the requirements (Richthofen et al., 2022).

Experts and skilled resources are crucial to the implementation process and help the new system be implemented successfully (Pradhananga et al., 2021). Experts help staff members use the new system and offer the support they need, which boosts their confidence in implementing it (BenMessaoud et al., 2011). Another important aspect of AI adoption is the accessibility of educational materials (Simões et al., 2020). Employees can acquire the abilities needed to operate new AI systems through awareness and training sessions (Yu et al., 2022).

If workers believe an AI system can solve complicated problems and boost productivity, they might be encouraged to utilize it (Kinkel et al., 2022). Adoption and implementation of AI systems are influenced by how operations are managed and carried out with internal and external stakeholders (Regona et al., 2022). Ineffective operations lengthen processes, make decision-making more difficult, and have a detrimental effect on how personnel interact with recently installed systems. When operations are effective, employees are more likely to view the new system as helpful and simple to use (Chatterjee, Rana, et al., 2021).

By allowing workers to participate in the adoption process from the outset and assist in dispelling any worries or misunderstandings regarding the new system, such as the fear of losing their jobs (Richthofen et al., 2022), management practices can be changed to facilitate the adoption of AI.

promote efficient collaboration and communication among staff members. Establishing an innovative culture, a collaborative culture among employees, and an effective decision-making process all depend heavily on management (Phuoc, 2022). As a result, workers are more inclined to interact with the new system and are less worried about it (Kar et al., 2021). Employee perceptions and intentions to adopt the new system are influenced by management support (Tjebane et al., 2022). Adopting AI systems necessitates strategic choices on planning, investments, resource distribution, organizational structure and policy changes (Tjebane et al., 2022), and other factors.

3.3. Environmental factors

The term "environmental factors" refers to external variables, like customer pressure, competitive marketplaces, and government assistance, that affect the adoption of AI. The environmental elements that affect the uptake of AI are discussed.

3.3.1. Firm-level influencing environmental factors

Competitive pressure, market instability, skilled resources in the market, market demand, industry and governmental laws, government assistance, political issues, the availability of AI vendors, and corporate social responsibility are some of the environmental elements that have an impact at the firm level. Organizational adoption decisions at the firm level are impacted by market uncertainty (Phuoc, 2022) and competitive pressure (Pizam et al., 2022). In order to anticipate market developments and maintain competitiveness, these environmental factors drive organizations to implement cutting-edge technologies (Kinkel et al., 2022).

To properly deploy and manage AI systems and support the organization's effective use of the technology, skilled personnel are essential. Therefore, one of the main factors influencing an organization's decision to implement AI systems is the availability of qualified personnel in the market (Wang and Su, 2021). When an organization decides to implement a new system, meeting market expectations is a crucial factor. Businesses use AI systems to meet customer expectations and enhance services, goods, or customer communication (Dora et al., 2021).

Adoption of AI systems is significantly influenced by government rules (Kumar et al., 2021) and industry regulations (Bademosi and Issa, 2021). Ethics, laws (Kumar et al., 2021), privacy and security laws (Yu et al., 2022), and economic laws (Chen et al., 2021) are examples of governmental regulations. By lowering adoption obstacles and promoting the adoption of new technologies, government laws can help organizations adopt cutting-edge technologies. Regulations may address privacy, security, and ethical issues (Phuoc, 2022). AI suppliers are another element impacting the adoption of AI in organizations (Al Badi et al., 2022). AI systems can be successfully adopted if reliable vendors are available and effective and transparent relationships exist between the organisation and vendors .

3.3.2. Environmental factors that influence at both the Firm-level and individual-levels

AI vendor support and business partner support are environmental elements that impact AI adoption at both the company and individual levels. Businesses like to use dynamic vendors because they offer ongoing updates that improve the performance of their AI systems. Operational stability depends on ongoing system maintenance, advancements, and updates (Al Badi et al., 2022). Decisions about the use of AI are also influenced by an organization's commercial partners. Organizations may face pressure to implement new technology from suppliers, IT providers, and/or other organizations like financial institutions and research centers (Simões et al.,2020).

Business partners' assistance improves an organization's performance and enables it to gain expertise. Additionally, business partners help staff members comprehend the advantages and usefulness of AI systems. As a result, business

partners help firms and individuals adopt AI (Chatterjee, Rana, et al., 2021).

3.4. Technological factors

The support of business partners enhances an organization's performance and allows it to acquire expertise. Business partners also assist employees in understanding the benefits and applications of AI technologies. Consequently, business partners assist companies and individuals in using AI (Chatterjee, Rana, et al., 2021).

3.4.1. Firm-level influencing technological factors

Return on investment (Baumgartner et al., 2022), the cost of AI systems (Law et al., 2022), the advantages of AI systems (Agarwal, 2022), technology integration (Kalyanaraman et al., 2022), compatibility with IT infrastructure (Na et al., 2022), system maturity (Golightly et al., 2022), and system accuracy and reliability (Campion et al., 2022) are some of the firm-level influencing technological factors.

Adoption of AI has a number of costs for businesses, including installation, operation, and maintenance expenses (Pramod, 2022; Bademosi and Issa, 2021). According to Kalyanaraman et al. (2022), the implementation of artificial intelligence may present a financial challenge for organizations because it may necessitate the adoption of new business models and technologies, the upgrading of current IT infrastructure, or the construction of new infrastructure, all of which require substantial financial investments. It is also necessary to pay for adoption-related expenses including system and implementation expenditures (Tjebane et al., 2022). Therefore, an organization's decision to employ AI technologies is heavily influenced by the adoption and implementation costs (Pillai and Sivathanu, 2020).

Businesses can boost productivity, cut expenses, improve operational performance, and expedite organizational procedures with the use of AI technology (Chen et al., 2021). The prospective advantages of an AI system affect a company's decision to implement it (Chen et al., 2021). Furthermore, integrating an AI system with an organization's current technology is necessary for AI adoption (Kalyanaraman et al., 2022). Adoption decisions are heavily influenced by how well the new AI system works with the existing infrastructure (Phuoc, 2022). Organizational adoption decisions are influenced by a new system's maturity. Organizations are worried about the dangers of artificial intelligence systems (Kinkel et al., 2022).

3.4.2. Technological factors at Firm-level and individual-level factors

System complexity (Du and Gao, 2022), privacy and security (Al Badi et al., 2022), trust in technology (Campion et al., 2022), and task-technology fit (Pizam et al., 2022) are the technological aspects that have an impact on businesses and individuals. Organizations should take into account the system's implementation and complexity (Pramod, 2022). Complex AI systems require more time and money to implement (Phuoc, 2022). Employee attitudes regarding a new system are also influenced by its complexity. A system is easier to use and more likely to be embraced by staff if its features and interfaces are simple.

Because of worries about how hard it will be to learn and operate the new system, employees' intention to utilize it may also be negatively impacted by its complexity (Yu et al., 2022).

Concerns about security and privacy may arise when organizations adopt and use AI (Singh et al., 2020). AI adoption and usage decisions are influenced by information privacy and the dangers of data sharing, which may also have an impact on the degree of confidence in AI (Brooks et al., 2020). AI systems may use sensitive data that includes user or customer personal and organizational information. As a result, businesses are worried about the security precautions that should be implemented to shield their data from potential thefts and cyberattacks. Employees' opinions of the AI system and their choices to use it are influenced by their level of trust in technology (Choi et al., 2022).

4. Discussion and implications

In order to determine the factors influencing AI adoption in organizations, this study examined the literature on the subject. The elements are divided into individual, societal, organizational, environmental, and technological factors, as was covered before. As a result, our study suggests a model that describes the factors influencing AI adoption at the corporate and employee levels. The premise that the factors influencing AI adoption at the firm and employee levels are independent is contested in this model. We separated the TOE elements into influencing factors at the corporate and individual levels.

Only the decision to implement AI systems at the company level (managers' choice to invest) is influenced by the former. Only managers' decisions to invest in AI systems are influenced by these considerations; employees' decisions to use them are unaffected. Managers' and employees' decisions to invest in and use AI systems are influenced by factors at both the corporate and individual levels.

5. Theoretical and practical contributions

5.1. Theoretical contribution

This study adds to the body of literature in a number of ways. First, this study summarized the results of earlier research and emphasized the factors that influence AI adoption at the company and employee levels. These results offer a thorough understanding of the factors influencing AI adoption. These elements were divided into three categories: societal, individual, and TOE. Second, we added to the body of research by demonstrating that TOE factors affect workers' choices to use AI systems. The study divided TOE elements into influencing factors at the corporate and individual levels. Businesses' decisions to use AI are influenced by both individual and firm-level considerations. Employee attitudes and views of AI systems may be shaped by individual-level influencing variables, which may then influence their decision to embrace them.

5.2. Practical contribution

AI systems have the ability to assist managers in making judgments and enhance their strategic decision-making process. However, the adoption of AI systems in organizations is heavily influenced by human behaviors toward new AI systems, managers' skills, and the perceived usefulness and simplicity of use (Oppioli et al., 2023). By examining the factors that influence AI acceptance and expanding managers' knowledge of AI adoption in organizations, this study advances practice in a number of ways.

First, managers may make well-informed decisions by taking into account the resources and capabilities of their companies as well as the business environment when they are aware of the elements that should be taken into account throughout the adoption stage. Additionally, by comprehending the factors that influence their employees' attitudes and behaviors toward AI systems, managers can successfully adopt AI systems. For example, avoiding the adoption of complex software may derive from understanding that system complexity may cause employee resistance during installation. Additionally, it might motivate managers to create thorough training courses and ongoing support systems so that staff members feel encouraged to embrace AI.

Additionally, AI system designers recognize the significance of creating intuitive and user-friendly user interfaces. Second, this review helps managers comprehend how organizational, technological, and environmental aspects affect workers' intentions to use AI systems. Businesses can create efficient management techniques to support AI adoption and implementation within their organizations by recognizing the impact of TOE elements in addition to personal and social considerations. Organizations can use a variety of managerial strategies to address adoption obstacles and issues and speed up the adoption process. Establishing an innovative and collaborative culture to encourage employees to accept and use the new systems, defining clear roles and responsibilities, and making sure that

the skilled resources (expertise) can provide support are all examples of managerial practices.

Establishing an innovative and collaborative culture to encourage employees to accept and utilize the new systems, defining clear roles and responsibilities, and ensuring that the skilled resources (expertise) can provide sufficient support for the employees are all examples of managerial practices.

6. Limitations and directions for future research

There are certain limitations to this evaluation that should be noted. First, only journal papers were included in the selection process. Because journal articles are regarded as "certified knowledge," using them improves the results' dependability. Future studies, however, might want to look into other kinds of publications, like books, reports, and conference proceedings. Second, because of its vast size, the Scopus database was selected for the compilation of articles. However, in order to expand the analysis and improve the outcomes, future studies should investigate other databases such as ProQuest, Web of Science, and EBSCO

Additionally, this study gives up new avenues for adoption literature research. We were able to uncover a number of research gaps and suggest future study areas by reviewing studies on the factors that influence AI adoption in organizations.

• Previous research on AI adoption has mostly concentrated on the firm-level factors that affect AI adoption. The elements that affect employees' intentions to use AI systems, however, have received less attention. Future research is needed to examine the factors that influence employees' intention to use AI systems because a significant percentage of AI adoption projects fail at the implementation stage (Makarius et al., 2020).

• Few studies on AI adoption have employed person-level theories, including TAM and UTAUT, to explain the factors influencing AI adoption at the employee level, similar to earlier research on technology adoption at the individual level. Our analysis shows that TOE elements may also have an impact on employees' emotions and perceptions, which may then have an impact on their choices about using AI systems. It is advised that future research examine how TOE factors affect workers' attitudes, behaviors, feelings, and perceptions.

• The literature has demonstrated how employee perceptions and emotions affect their intention to use AI technologies. Nonetheless, research has presumed that workers are uniform and that the effects of various factors are comparable. In actuality, employees have different demands and traits, and their adoption decisions are influenced by different elements. Future research should therefore take employee heterogeneity into account and examine the moderating effects of individual traits like self-efficacy, personal inventiveness, and a propensity to share knowledge.

• The majority of research on the factors influencing AI adoption makes the assumption that the decision to embrace AI is logical and is impacted by practical considerations like usefulness and ease of use. However, hedonic and social factors play important roles in individuals' adoption decisions. Therefore, in addition to functional variables, it is advised that future studies evaluate the importance of hedonic and social factors, such as reported enjoyment and social contact.

• It is anticipated that the variables affecting the adoption of AI would interact with one another. Furthermore, depending on a variety of situations, including the organization, industry, and social environment, some elements may predominate over others. We suggest the following lines of inquiry for future studies that aid in addressing the intricacies and interdependencies of the AI adoption variables in order to close this knowledge gap about the interactions among factors driving AI adoption: Future research should focus on quantitatively evaluating each factor's influence on the adoption of AI. Both need to comprehend how strong these effects are.

Academics and professionals. The Artificial Neural Network (ANN) technique is suggested for this purpose since it enables the factors to be ranked according to their relative relevance.

It is advised that the issues be prioritized according to how they affect the adoption of AI. Decision-makers will gain important insights from this prioritization while developing plans. An efficient technique for this kind of ranking is the Analytic Hierarchy Process (AHP), which uses expert opinions to assess the relative significance of each component.

Future research is needed to investigate and identify intricate interaction patterns to understand how combinations of factors affect AI adoption. For this aim, fuzzy-set qualitative comparative analysis (fsQCA) is advised since it enables the analysis of how various factor combinations result in different outcomes.

In order to provide a thorough understanding of the AI adoption process and help managers and academics make decisions, future research must show the interrelationships between various aspects. It is advised to use Multi-Criteria Decision Making (MCDM) techniques like the Adaptive Neuro-Fuzzy Inference System (ANFIS). ANFIS, which combines the benefits of fuzzy logic and neural networks, is especially well-suited for modeling intricate, non-linear interactions.

Conclusion,

The principal aim of this research endeavor was to synthesize the extant literature concerning the determinants influencing the adoption of artificial intelligence (AI) and to delineate pathways for prospective investigations. In pursuit of the objectives delineated in this study, a review of many scholarly articles pertaining to the determinants of AI adoption was conducted. The research systematically categorized the factors influencing AI adoption into distinct domains: individual, social, technological, organizational, and environmental elements. As illustrated, factors at the organizational level also exert an influence on employees' behaviors regarding AI systems, which we refer to as individual-level Technology-Organization-Environment (TOE) influencing factors. The ramifications of these factors on employees' perceptions, emotional responses, and behaviors towards emergent technologies necessitate further scholarly inquiry. This study posited a model of AI adoption that elucidates the potential interrelations among individual and social, organizational, environmental, and technological factors. Additional research is imperative to evaluate this model across diverse contextual frameworks. The study elucidates both the facilitators and impediments to AI adoption at both the individual and organizational levels, thereby offering guidance for organization's managers.

References:-

Alghamdi, M.I. (2020), "Assessing factors affecting intention to adopt AI and ML: The case of the Jordanian retail industry", Periodicals of Engineering and Natural Sciences (PEN), Vol. 8 No. 4, pp. 2516–2524.

Alshare, K.A., Alomari, M.K., Lane, P.L. and Freeze, R.D. (2019), "Development and determinants of end-user intention: usage of expert systems", Journal of Systems and Information Technology, Vol. 21 No. 2, pp. 166–185, doi: 10.1108/JSIT-08-2018-0108.

Tjebane, M.M., Musonda, I. and Okoro, C. (2022), "Organisational Factors of Artificial Intelligence Adoption in the South African Construction Industry", Frontiers in Built Environment, Vol. 8, doi: 10.3389/fbuil.2022.823998.

Bawack, R.E., Wamba, S.F., Carillo, K.D.A. and Akter, S. (2022), "Artificial intelligence in E-Commerce: a bibliometric study and literature review", Electronic Markets, Vol. 32 No. 1, pp. 297–338, doi: 10.1007/s12525-022-00537-z.

Bedué, P. and Fritzsche, A. (2022), "Can we trust AI? An empirical investigation of trust requirements and guide to successful AI adoption", Journal of Enterprise Information Management, Vol. 35 No. 2, pp. 530–549, doi: 10.1108/JEIM-06-2020-0233.

BenMessaoud, C., Kharrazi, H. and MacDorman, K.F. (2011), "Facilitators and Barriers to Adopting Robotic-Assisted Surgery: Contextualizing the Unified Theory of Acceptance and Use of Technology", edited by McCulloch, P.PLoS ONE, Vol. 6 No. 1, p. e16395, doi: 10.1371/journal.pone.0016395.

Oppioli, M., Sousa, M.J., Sousa, M. and de Nuccio, E. (2023), "The role of artificial intelligence for management decision: a structured literature review", Management Decision, doi: 10.1108/MD-08-2023-1331.

Makarius, E.E., Mukherjee, D., Fox, J.D. and Fox, A.K. (2020), "Rising with the machines: A sociotechnical framework for bringing artificial intelligence into the organization", Journal of Business Research, Vol. 120, pp. 262–273, doi: 10.1016/j.jbusres.2020.07.045.

Cao, G., Duan, Y., Edwards, J.S. and Dwivedi, Y.K. (2021), "Understanding managers' attitudes and behavioral intentions towards using artificial intelligence for organizational decision-making", Technovation, Vol. 106, p. 102312, doi: 10.1016/j.technovation.2021.102312.

Chatterjee, S., Chaudhuri, R., Vrontis, D., Thrassou, A. and Ghosh, S.K. (2021), "Adoption of artificial intelligence-integrated CRM systems in agile organizations in India", Technological Forecasting and Social Change, Vol. 168, p. 120783, doi: 10.1016/j.techfore.2021.120783.

Dabbous, A., Aoun Barakat, K. and Merhej Sayegh, M. (2022), "Enabling organizational use of artificial intelligence: an employee perspective", Journal of Asia Business Studies, Vol. 16 No. 2, pp. 245–266, doi: 10.1108/JABS-09-2020-0372.

Chocarro, R., Cortiñas, M. and Marcos-Matás, G. (2021), "Teachers' attitudes towards chatbots in education: a technology acceptance model approach considering the effect of social language, bot proactiveness, and users' characteristics", Educational Studies, pp. 1–19, doi: 10.1080/03055698.2020.1850426.

Choi, S., Jang, Y. and Kim, H. (2022), "Influence of Pedagogical Beliefs and Perceived Trust on Teachers' Acceptance of Educational Artificial Intelligence Tools", International Journal of Human–Computer Interaction, pp. 1–13, doi: 10.1080/10447318.2022.2049145.

Dora, M., Kumar, A., Mangla, S.K., Pant, A. and Kamal, M.M. (2021), "Critical success factors influencing artificial intelligence adoption in food supply chains", International Journal of Production Research, pp. 1–20, doi: 10.1080/00207543.2021.1959665.

Du, Y. and Gao, H. (2022), "Determinants affecting teachers' adoption of AI-based applications in EFL context: An analysis of analytic hierarchy process", Education and Information Technologies, doi: 10.1007/s10639-022-11001-y.

Kinkel, S., Baumgartner, M. and Cherubini, E. (2022), "Prerequisites for the adoption of AI technologies in manufacturing – Evidence from a worldwide sample of manufacturing companies", Technovation, Vol. 110, p. 102375, doi: 10.1016/j.technovation.2021.102375.

Pietronudo, M.C., Croidieu, G. and Schiavone, F. (2022), "A solution looking for problems? A systematic literature review of the rationalizing influence of artificial intelligence on decision-making in innovation management", Technological Forecasting and Social Change, Vol. 182, p. 121828, doi: 10.1016/j.techfore.2022.121828.

Pradhananga, P., ElZomor, M. and Santi Kasabdji, G. (2021), "Identifying the Challenges to Adopting Robotics in the US Construction Industry", Journal of Construction Engineering and Management, Vol. 147 No. 5, doi: 10.1061/(ASCE)CO.1943-7862.0002007.

Secinaro, S., Calandra, D., Secinaro, A., Muthurangu, V. and Biancone, P. (2021), "The role of artificial intelligence in healthcare: a structured literature review", BMC Medical Informatics and Decision Making, Vol. 21 No. 1, p. 125, doi: 10.1186/s12911-021-01488

Di Vaio, A., Palladino, R., Hassan, R. and Escobar, O. (2020), "Artificial intelligence and business models in the sustainable development goals perspective: A systematic literature review", Journal of Business Research, Vol. 121, pp. 283–314, doi: 10.1016/j.jbusres.2020.08.019.

Han, J. and Conti, D. (2020), "The Use of UTAUT and Post Acceptance Models to Investigate the Attitude towards a Telepresence Robot in an Educational Setting", Robotics, Vol. 9 No. 2, p. 34, doi: 10.3390/robotics9020034.

Hogan, J., Grant, G., Kelly, F. and O'Hare, J. (2020), "Factors influencing acceptance of robotics in hospital pharmacy: a longitudinal study using the Extended Technology Acceptance Model", International Journal of Pharmacy Practice, Vol. 28 No. 5, pp. 483–490, doi: 10.1111/ijpp.12637.

Jöhnk, J., Weißert, M. and Wyrtki, K. (2021), "Ready or Not, AI Comes— An Interview Study of Organizational AI Readiness Factors", Business & Information Systems Engineering, Vol. 63 No. 1, pp. 5–20, doi: 10.1007/s12599-020-00676-7.

Kalisz, D.E., Khelladi, I., Castellano, S. and Sorio, R. (2021), "The adoption, diffusion & categorical ambiguity trifecta of social robots in e-health – Insights from healthcare professionals", Futures, Vol. 129, p. 102743, doi: 10.1016/j.futures.2021.102743.

Kinkel, S., Baumgartner, M. and Cherubini, E. (2022), "Prerequisites for the adoption of AI technologies in manufacturing – Evidence from a worldwide sample of manufacturing companies", Technovation, Vol. 110, p. 102375, doi: 10.1016/j.technovation.2021.102375.

Kopp, T., Baumgartner, M. and Kinkel, S. (2021), "Success factors for introducing industrial human-robot interaction in practice: an empirically driven framework", The International Journal of Advanced Manufacturing Technology, Vol. 112 No. 3–4, pp. 685–704, doi: 10.1007/s00170-020-06398-0.

Latikka, R., Turja, T. and Oksanen, A. (2019), "Self-efficacy and acceptance of robots", Computers in Human Behavior, Vol. 93, pp. 157–163, doi: 10.1016/j.chb.2018.12.017.

Law, K.K., Chang, S. and Siu, M.-F.F. (2022), "Factors Influencing Adoption of Construction Robotics in Hong Kong's Industry: A Multistakeholder Perspective", Journal of Management in Engineering, Vol. 38 No. 2, doi: 10.1061/(ASCE)ME.1943-5479.0001011.

Victor Mugabe, K. (2021), "Barriers and facilitators to the adoption of artificial intelligence in radiation oncology: A New Zealand study", Technical Innovations & Patient Support in Radiation Oncology, Vol. 18, pp. 16–21, doi: 10.1016/j.tipsro.2021.03.004.

Page, M.J., McKenzie, J.E., Bossuyt, P.M., Boutron, I., Hoffmann, T.C., Mulrow, C.D., Shamseer, L., et al. (2021), "The PRISMA 2020 statement: an updated guideline for reporting systematic reviews", BMJ, p. n71, doi: 10.1136/bmj.n71.

Pan, J., Ding, S., Wu, D., Yang, S. and Yang, J. (2019), "Exploring behavioural intentions toward smart healthcare services among medical practitioners: a technology transfer perspective", International Journal of Production Research, Vol. 57 No. 18, pp. 5801–5820, doi: 10.1080/00207543.2018.1550272.

Ramos-Rodríguez, A. and Ruíz-Navarro, J. (2004), "Changes in the intellectual structure of strategic management research: a bibliometric study of the Strategic Management Journal , 1980–2000", Strategic Management Journal, Vol. 25 No. 10, pp. 981–1004, doi: 10.1002/smj.397.

Turja, T. and Oksanen, A. (2019), "Robot Acceptance at Work: A Multilevel Analysis Based on 27 EU Countries", International Journal of Social Robotics, Vol. 11 No. 4, pp. 679–689, doi: 10.1007/s12369-019-00526-x.

Wang, Y. and Su, X. (2021), "Driving factors of digital transformation for manufacturing enterprises: a multi-case study from China", International Journal of Technology Management, Vol. 87 No. 2/3/4, p. 229, doi: 10.1504/IJTM.2021.120932.

Yang, Y., Chan, A.P.C., Shan, M., Gao, R., Bao, F., Lyu, S., Zhang, Q., et al. (2021), "Opportunities and Challenges for Construction Health and Safety Technologies under the COVID-19 Pandemic in Chinese Construction Projects", International Journal of Environmental Research and Public Health, Vol. 18 No. 24, p. 13038, doi: 10.3390/ijerph182413038.