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The Influence of the Expected Factors for Adopting Artificial Intelligence Applications in Firms' Management

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The aim of this dissertation is to obtain a doctoral (PhD) degree in the scientific field of „Management and Business"

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- No dissertation which is fully or partly identical to the present dissertation was submitted to any other university or doctoral school for the purpose of obtaining a PhD degree.

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LIST OF ABBREVIATION

AGI = Artificial General Intelligence

AI = Artificial Intelligence

ANI =Artificial Narrow Intelligence

ANNs = Artificial Neural Networks

APIs = Application programming interfaces

ASI = Artificial Super Intelligence

CC = Cloud Computing

CPS = Cyber-Physical Systems

DOI = Diffusion of Innovation

I4.0 = Industry 4.0

ICTs = Information and Communication Technologies

IEEE = Institute of Electrical and Electronics Engineers

IoT = Internet of Things

IS = Information System

IT = Information Technology

IVR = Interactive Voice Response

KMS = Knowledge Management Systems

ML = Machine Learning

NLP = Natural Language Processing

NPD = New Product Development

NSTC = National Science and Technology Council

QFD = Quality Function Deployment

TAM = Technology Acceptance Model

TOE = Technology, Organization, and Environment framework

INTRODUCTION

In the contemporary business landscape, firms are confronted with a myriad of challenges stemming from the dynamic nature of the global marketplace, including globalization, heightened competition, evolving consumer expectations, diversification, and most recently, the disruptive impacts of the COVID-19 crisis (ODEIBAT, 2021; THOMAS, 2014; PING et al., 2018; AIER et al., 2022). To navigate these complexities and maintain a competitive edge, companies have increasingly turned to technological innovation to enhance their traditional management strategies and practices (TURKULAINEN et al., 2017).

The pivotal role of technology adoption in bolstering firms' performance and competitiveness has been widely recognized in academic discourse (NOVAKOVA, 2020; SCHWAB, 2017). Previous empirical studies have underscored the positive correlation between technology adoption and business performance, citing benefits such as operational enhancements, revenue growth, and improved efficiency (ALMEHAIRBI et al., 2022; FERRER-DÁVALOS, 2023; ASSER et al., 2023). Technologies, such as information and communication technologies (ICTs) and digital tools, have been instrumental in driving productivity gains, enhancing competitiveness, and augmenting customer satisfaction across various industries (ZHOU et al., 2023; CUEVAS VARGAS et al., 2021).

Artificial Intelligence (AI), in particular, has emerged as a transformative force reshaping organizational processes and functions, heralding what some scholars have termed as the fourth industrial revolution (SCHWAB, 2017). The proliferation of AI technologies across diverse sectors, including engineering, telecommunications, finance, healthcare, and customer service, underscores its pervasive influence on contemporary business operations (PING et al., 2018). Yet, the advent of AI presents a dualistic narrative concerning the roles of machines and humans in the workforce. While AI holds the promise of streamlining tasks, enhancing productivity, and improving living standards, it also raises questions about the displacement of human labour and the ethical implications of machine autonomy (El-Homsi, 2018).

Artificial Intelligence can be divided into different types: Artificial General Intelligence (AGI), Artificial Super Intelligence (ASI) and Artificial Narrow Intelligence (ANI)(EL-HOMSI, 2018). This research focuses mainly on Artificial Narrow Intelligence to achieve the study goals. When AI can be defined as “a system’s ability to interpret external data correctly, to learn from such data, and to use that learning to achieve specific goals and tasks through flexible adaption” (KAPLAN & HAENLEIN, 2019). Companies started to use AI robotics in production to automate tedious and complex job tasks (LUCCI & KOPEC, 2016; EL-HOMSI, 2018; HMOUD & LASZLO, 2019).

Certainly, the impact of modern technologies can be found on humans life by making it more convenient and easier, decreasing the need for physical humans in dangerous jobs and tedious work, and improving overall living standards (BRYNJOLFSSON & MCAFEE, 2014; IVANOV et al., 2020; EL-HOMSI, 2018; DREXLER, 2013). Artificial intelligence can be found everywhere, for example, individuals use many smart digital assistant applications such as Google Assistant, Amazon Alexa, Apple Siri, Samsung Bixby, and other digital assistants that make life easier and save time and effort (PURWANTO et al., 2020). In addition, companies have started to adopt modern technology to automate tasks, which will change the employees' job roles; they are also likely to replace humans or work alongside with them. For example, a cashier, shop assistant, and other jobs (EL-HOMSI, 2018; MAKARIUS et al., 2020). Much research has argued about the machines' ability to act like humans. In contrast, others doubt about that highly sophisticated behaviour, like morality, love, or creativity, will always be beyond machines' capabilities (NOVAKOVA, 2020; NEGNEVITSKY, 2005). AI is wielding a deep influence on the global economy, humans' daily life and social growth. GHOSH et al., (2019) stated in their research that the adoption of Artificial Intelligence technologies in big companies increased as around 80 % of the companies started to integrate AI technologies in their work in the last five years. Artificial intelligence will likely to play an essential role in the future of jobs and organizations' performance because it is present in most of the organizational functions (WILSON et al., 2019; HUANG & RUST, 2018). Recently, AI has been able to forecast choices, initiate complex codes, create solutions, mine billions of data, and react with humans in real-time. AI technologies like machine learning, natural language processing, and deep learning propose highly advanced data analysis abilities to current applications in various industries and facilitate companies' operations, planning, and management (KASEMSAP, 2017).

Therefore, companies adopt Artificial intelligence technologies into their work environment to obtain their benefits like improving performance and efficiency, developing long-term automation strategies, cost reduction, saving effort and time, improving strategic outcomes, decreasing errors, improving decision making, eliminating human bias, causing less pressure on human resources and re-creation of the customer experience and enhancing sustainability and competitiveness (DAVENPORT & KIRBY, 2015; MAKARIUS et al., 2020; DAVENPORT et al., 2020; PASCHEN et al., 2020; SYED et al., 2020; HMOUD & LASZLO, 2019; ALSHEIBANI et al., 2018; EL-HOMSI, 2018). Additionally, SCHILLEWAERT and

AHEARNE (2015) stated in their practical study that there is a positive effect of using modern technology on salesforce performance, which results in high performance through increased technical knowledge, market data, adaptive selling, targeting skills, presentation skills, and overall productivity. According to (BUGHIN & HAZAN, 2019; DAVENPORT et al., 2020), economic growth and productivity improvement have a potentially positive relationship with technology adoption in firms. They also mentioned that to accomplish a successful technology adoption. It requires better trained, healthy, less stressed employees to be more active, more productive, and able to direct the adoption of technology to boost the profits and revenues at the firm’s level. In addition, it will demand cooperation from different sectors such as the public sector and business leaders. Also, the COVID-19 pandemic crisis forces firms to adopt technology to cope with remote work and the new business environment (MAKARIUS et al., 2020). For example, 84% percent of business managers are obliged to rapidly digitalize operational processes involving remote work, with the possibility to move 44% percent of their workers to work remotely (SCHWAB & ZAHIDI, 2020). Chatbots and robots have been used in different jobs, such as customer communication and reception, to deliver high safety for employees who may react in complicated cases only (SIGALA, 2020). Although Artificial Intelligence is promising and has great benefits, it is not always the case as it is still in the infancy stage, and it is sensible to estimate that leaders are not confident in adopting it (CANHOTO & CLEAR, 2020). Also, not all companies have started to apply it due to many challenges such as, the companies’ culture not yet recognizing the need for AI, the lack of skilled employees and data, the lack of ability to use the technology, and the complications of hiring expert employees and the difficulties restructure their systems and process (LICHTENTHALER, 2018; GLIKSON & WOOLLEY, 2020).

The DELOITTE (2017) survey indicated that forty-seven percent of senior leaders working in 152 Artificial Intelligence projects face difficulties integrating AI technology with systems, employees, structure and process inside the companies. Similarly, a quote from Bill Gates "whereby automating an inefficient process merely magnifies its inefficiency," concludes the importance of adoption the suitable technology that fit into the company to reach the maximum advantage and avoid any default. To achieve successful adoption, it is crucial to requalify the employees to prepare sufficient training and development strategies to integrate them with the new technology. As well as the firms must be ready for new revolution by restructuring their systems, process, and arrangement based on innovative technology requirements (MAKARIUS et al., 2020; GLIKSON & WOOLLEY, 2020; LACITY et al., 2016; LICHTENTHALER, 2018). Otherwise, the sudden reaction and quick adoption of AI indicate that there might be a considerable degree of risk that could create negative effects that could eventually harm the company. The current literature has established the impact of information technology adoption and specified their success factors (KIM et al., 2010; OLIVEIRA & MARTINS, 2011). In addition, it has studied the implementation process of firms adopt IT innovations. Previous literature research on AI mostly emphasis applications and techniques (WALCZAK, 2016; QI, et al., 2007). However, managerial concerns about AI, mainly, the factors that affect AI's successful adoption, are overlooked. There is a limitation on the empirical studies that confirm the direct and the indirect impacts of AI characteristics and the effects of the implied technology, environment, and organization. Accordingly, this dissertation endeavours to explore the factors influencing the adoption of AI technologies in telecommunication firms. The telecommunications industry has evolved significantly since 2000, shifting from traditional voice services to data-centric networks. This shift has led to challenges in digital transformation, as companies face increased demand for faster data and competition from web-based companies. To address these issues, telecom operators are adopting technologies like IoT and 5G, which bring complexities in network management. AI is becoming crucial for efficient operations, with telecom companies exploring AI-driven solutions to enhance both customer services and internal systems (CASTRO et al., 2018; XU & DUAN, 2018; ZHANG & LORENZ, 2018). To examine the impacts of success factors on AI adoption in firms, this research will integrate the diffusion of innovation (DOI) theory (ROGERS, 1995) and the technology, organization, and environment (TOE) framework (TORNATZKY & FLEISCHER, 1990). Previous literature in innovation, implementation, diffusion, and adoption of information technology identified ten success factors related to AI adoption based on the previously reviewed IT adoption studies.

Drawing upon the Diffusion of Innovation (DOI) theory and the Technology-Organization-Environment (TOE) framework, this study examine the interplay between organizational capabilities, innovation attributes, and external environmental factors in influencing AI adoption. Specifically, factors such as managerial support, organizational readiness, compatibility, relative advantage, market uncertainty, competitive pressure, government involvement, and vendor partnerships will be scrutinized to ascertain their impact on AI adoption in firms. To empirically validate the proposed framework, data will be gathered through an online questionnaire from the telecommunications companies in Hungary. By identifying the critical success factors and impediments to AI adoption, this dissertation provides practitioners, policymakers, and scholars with actionable insights to optimize AI integration strategies and maximize its benefits. In summary, this study aims to contribute to understanding AI adoption dynamics within businesses by providing a structured framework to guide future research and foster innovation in the rapidly evolving digital landscape.

1. TOPICS AND OBJECTIVE

This chapter summarizes these research gaps into a precise aim, objectives, and research questions, serving as the foundation to guide the subsequent phases of the study and aiding in the evaluation of study findings. Additionally, it offers a brief overview of the research hypotheses and methodology.

1.1 Research aims

This research aims to investigate the impact factors of AI adoption in firms. Also, establish a guide to the most effective factors of AI adoption in companies and highlight the top management roles in improving AI adoption and the integration of AI with human intelligence.

1.2 Research objectives

1. Identifies and evaluates the key factors influencing firms' adoption and usage of AI technologies.
2. Provides a comprehensive overview of each factor's varying levels of influence.
3. Analyze how AI adoption influences firms' management practices across various departments and functions.
4. Offers tailored recommendations for optimizing management strategies in response to AI implementation.
5. Investigate the role of leading management in driving AI adoption within firms.
6. Identifies opportunities for top management to adopt AI technologies effectively to maximize benefits.
7. Develops a framework for optimizing the benefits derived from AI adoption based on management's strategic decisions.

1.3 Research questions

To fully achieve the research goals, the subsequent inquiries have been created:

1. What factors influence firms' adoption and use of AI technologies?
2. To what extent will these factors impact AI adoption?
3. To what extent will these factors influence AI adoption? Will their level be the same?
4. How will AI adoption impact the firms’ management?

5. What is the top management's role in adopting AI, and how they will utilize it to optimize benefits?

1.4 Research hypotheses

Four main research hypotheses have been formulated To address the study questions. These hypotheses correspond to the three primary research constructs and their underlying hypotheses, which are elaborated upon in detail in Chapter 3, titled 'Research Model And Hypotheses Development,' and are detailed below:

1. Innovation attributes of AI: H1. AI's innovation attributes significantly influence leaders' attitudes toward AI adoption in telecom companies.

H1.1: Compatibility is significantly associated with AI adoption.

H1.2: Relative advantage is significantly associated with AI adoption.

H1.3: Complexity affects AI adoption negatively.

2. Organizational capability: H2. Organizational capability significantly influences leaders' attitudes toward AI adoption in telecom companies.

H2.1: Managerial support influences AI adoption positively.

H2.2: Technical capabilities positively affect AI adoption.

3. Managerial capabilities: H3. Managerial capabilities have a significant impact on organizational capability and the innovation attributes of AI

H3.1: Managerial capabilities affect the compatibility of AI positively.

H3.2: Managerial capabilities positively affect the relative advantage of AI.

H3.3: Managerial capabilities affect the complexity of AI negatively.

H3.4: Managerial capabilities influence the managerial support positively.

H3.5: Managerial capabilities are positively associated with technical capabilities.

4. External environment: H4. External environment significantly influences leaders' attitudes toward AI adoption in telecom companies.

H4.1: Government involvement is positively associated with AI adoption.

H4.2: Competitive pressure is positively influencing AI adoption.

H4.3: Market uncertainty is negatively associated with AI adoption.

H4.4: Vendor partnership is positively associated with AI adoption.

2. LITERATURE REVIEW

The following section provides an in-depth overview of the previous literature on the relevant research topic, including the definition and development of Artificial Intelligence (AI), modern technologies and applications of AI, and AI's main fields, such as machine vision, expert systems, natural language understanding, deep learning and machine learning. Additionally, Artificial Intelligence applications are discussed, including the most common artificial intelligence applications such as speech and voice services for customers and customer service chatbots. Furthermore, it involves studying the conceptual framework for AI adoption, which includes the previous literature on IT adoption and the theories and models of IT adoption.

2.1 Artificial intelligence definition and development

A few decades ago, Artificial Intelligence (AI) used to be theoretically seen in science fiction movies, but today, it has become a reality. For example, self-driving cars, navigation systems, virtual assistants, robots, computer vision, and medical chatbots, etc. (MAKRIDAKIS, 2017; RADHAKRISHNAN & GUPTA, 2020). Artificial intelligence arose in the twentieth century, along with the rise of computing technology (ODEIBAT, 2021; MEEK, et al., 2016). AI expression began to grow globally in 1995 after the appearance of the book "Artificial Intelligence: A Modern Approach" written by Stuart J. Russell and Peter Norvig (HMOUD & LASZLO, 2019). Artificial Intelligence (AI) is not new; early scientists implanted AI as an industry along with hardware development in the 1980s. The first AI term was introduced in a conference organized by John McCarthy in 1956 (EL-HOMSI, 2018). Figure 1 shows the AI evolution milestones and stages, and Figure 2 shows the evolution of AI over time.

Initially, AI was defined as computer processes used to create a complex machine with characteristics like human intelligence (STUART & PETER, 1995). The definition of AI has evolved with time, as there is no specific standard definition of it. LUGER (1993) described artificial intelligence as a part of computer science that is concerned with automating intelligent behaviors. AI encompasses the method that gives machines intelligent complexity. According to NILSSON (2014), AI encompasses the ability to impart intelligent attributes to machines. KASEMSAP (2017) mentioned that AI aids machines in discovering the best solution for complex problems in a human-like manner.PANNU (2015) states that AI outperforms natural intelligence because it is more consistent, lasts longer, is easier to copy and spread, is less expensive, and can perform and record specific tasks faster and better than humans. He claimed that AI is neither computer science nor psychology, encompasses perception, computation, action, and reasoning. EL-HOMSI (2018) defined AI as machine intelligence or software that can imitate human intelligence. From a managerial perspective, AI can be defined as an advanced set of technologies with the ability to interact with the surroundings through several key processes: (a) acquiring data from external sources, including natural language and other computer systems; (b) analysing this data by identifying patterns, deriving rules, or making predictions; (c) producing outcomes such as responses to queries or instructions for other systems; and (d) assessing the outcomes of their actions and enhancing their decision-making systems to attain particular goals (GLIKSON & WOOLLEY, 2020; FERRÀS-HERNÁNDEZ, 2018). The interactive nature of AI enables it to learn and adapt its behaviour according to environmental cues. AI implies the ability of machines to synthesize, perceive, and infer information, distinguishing it from the intelligence exhibited by non-human animals and humans (OLA, 2023).

Although scholars define artificial intelligence from different perspectives, they mainly agree that AI includes computer science, psychology, mathematics, information engineering, philosophy, and linguistics (PANNU, 2015). Additionally, its expression comprises problem-solving, investigating intelligence, and creating intelligent computer systems. The progression of AI undergoes three phases, delineated in Figure 1: the initial stage (infancy), which started in 1956 and lasted until 1980; the industrial phase from 1980 to 2000; and the third period (flourishing) from 2000 to 2018.

In Figure 2, we illustrate the progression of artificial intelligence development, where significant events are depicted at various points along the timeline. Additionally, the development of AI has been rapid. In 2023, it's likely to be remembered as one of the most tumultuous and eventful years in AI history. People were still grappling with the capabilities of OpenAI’s ChatGPT, which debuted in late 2022, when the company unveiled its latest large language model, GPT-4, in March 2023 (these models essentially power consumer-facing applications). Throughout the spring of 2023, prominent figures expressed concerns about the potential negative repercussions ranging from concern to potential catastrophic—of continually advancing AI. This led to various significant events, including an open letter advocating for a halt in advanced model development, a declaration regarding existential risks, the inaugural international summit on AI safety, and groundbreaking regulations such as a U.S. executive order and the E.U. AI Act (STRICKLAND, 2023). The European Commission released its proposed AI Act in 2021, and it is expected to be the first comprehensive AI law, aiming for finalization in 2024 (YAKIMOVA & OJAMO, 2023).

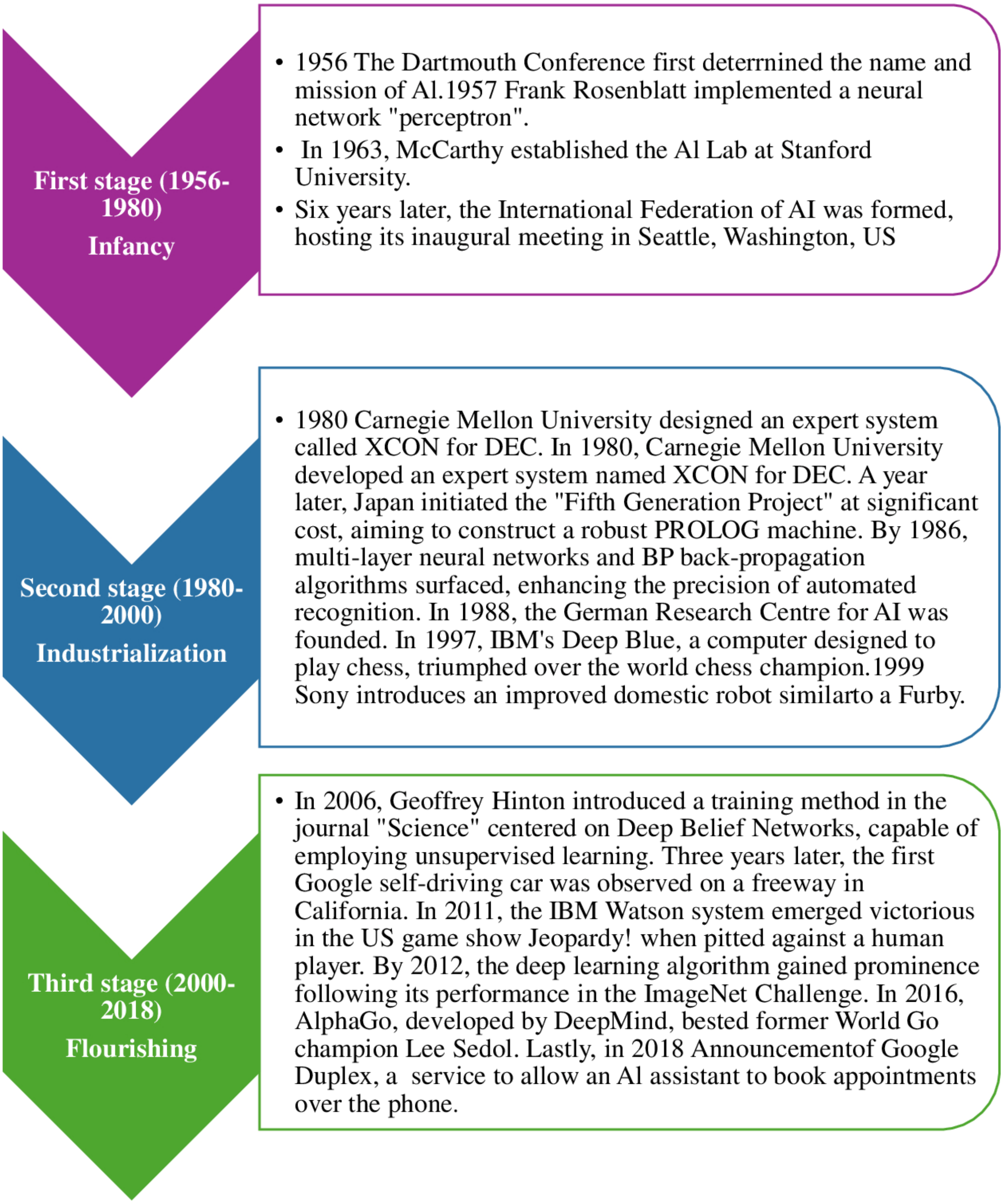

Figure 1. Artificial Intelligence Evolution Milestones (1956-2018)

Source: edited by Author from (CAICT & GARTNER, 2018)

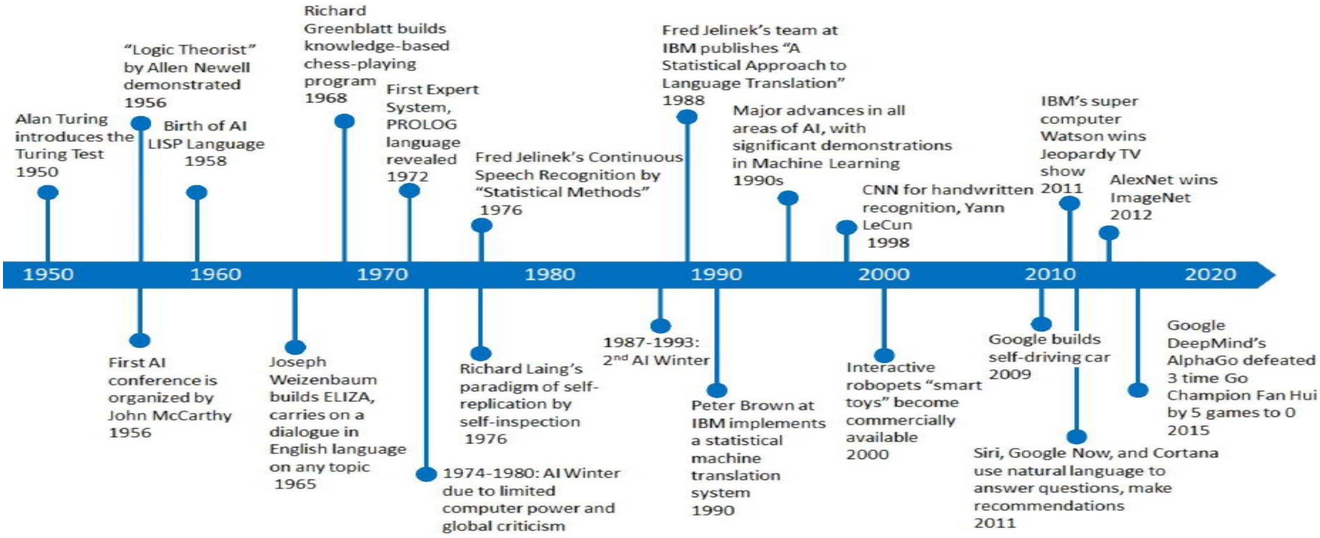

Figure 2. The Evolution of Artificial Intelligence over time

Sorce: (EL-HOMSI, 2018)

2.2 Modern technologies and AI main fields

Modern technologies include many examples, such as AI, IT applications, automation systems, industrial robots, digital assistant applications, chatbots, social and service robots, etc. These applications are employed in numerous sectors, including financial services, manufacturing production, process automation, customer service, healthcare, agriculture, automated border control, tourism, banks, ordinary life, etc. (MAKARIUS et al., 2020; IVANOV et al., 2020; ODEIBAT, 2021; PURWANTO et al., 2020). Industry 4.0 (I4.0) represents the most recent trend adopted by numerous companies to enhance their production and operational efficiency. Incorporating a variety of automation methods such as artificial intelligence (AI), cloud computing (CC), cognitive computing, Internet of Things (IoT), cyber-physical systems (CPS), and others, these new technologies collectively form what is known as a smart factory within a company. Many organizations strive to integrate these digital technologies due to the highly competitive nature of today's market, which provides a significant advantage to companies implementing Industry 4.0 practices (RAJAMANICKAM et al., 2023). In the 21st century, advancements in computer abilities, big data, and theoretical comprehension propel the advancement of AI technologies. Significant progress has been made in translating AI studies and technology into effective products. Despite the existence of various AI technologies for many years, the enhanced speed in network and data processing, along with hardware innovations, facilitate the availability of commercial AI applications.

2.2.1 Machine vision

Machine vision is a subset of AI that enables machines to perceive and comprehend their environment visually. This entails utilizing cameras and sensors to record and analyse images of tangible objects, extracting valuable insights from the visual data (HSIAO & SHOREY, 2023). According to CHEN (2016), machine vision, or computer vision technology, uses computers and cameras to substitute human vision, track, recognize objects, and process images. This makes computer processing more appropriate for human eyes watch or deliver images to a device. Machine vision is regarded as a fundamental aspect of AI technology. Additionally, it enables computers to achieve visual perception akin to human discernment, accurately recognizing image features with speed, precision, and accuracy.

Machine vision is used in autonomous driving vehicles, video monitoring, face recognition, aerial remote sensing measurements, and image analysis for medical purposes (BARCELO & DE ALMEIDA, 2012). Machine vision technology finds diverse uses, encompassing tasks like identifying objects, categorizing images, and detecting moving targets. Its deployment spans manufacturing, healthcare, and retail industries, facilitating automation, digital transformation, and enhanced operational efficiency. Integrating machine vision systems with robotics and deep learning methods enhances their functionality, empowering intelligent decision-making. Furthermore, the evolution of machine vision technology has driven progress in areas like medical diagnostics, airport security, and interactive rehabilitation systems for treating autism (FRIGENI, 2022; HSIAO and SHOREY, 2023; CAI and CHEN, 2022).

2.2.2 Expert system

The expert system stands out as among the initial triumphant AI applications. It represents one of AI's swiftly expanding and extensively employed technical avenues, as highlighted by RUSSELL and NORVIG (2016). Expert systems emulate human problem-solving capabilities as a subset of artificial intelligence by leveraging knowledge and rules (SYAHPUTRI, 2021). Expert systems include the inference engine, the knowledge base, and the user interface. It is a well-organized system built on information miming human expert problem-solving skills (PANNU, 2015). Therefore, an expert system utilizes stored knowledge to address problems, aiming to aid professionals in their tasks and empower individuals to tackle intricate issues independently (SAPUTRA, 2023). These systems assist organizations in identifying project complexities and devising effective solutions, thus augmenting the decision-making process of experts and enhancing operational efficiency (CHHAJER, 2021). Many companies have started to adopt expert systems as a first step in AI adoption. For example, XCON was the first successful expert system (MULLER et al., 1993). LIAO (2005) points out that the expert system underwent many changes over time; however, it still applied to solve complex problems. For example, they use the expert system in decision-making and solving problems. Also, the expert system can manage truths or heuristics and handle unreliable, missing, uncertain data (JAYARAMAN & SRIVASTAVA, 1996). In addition, In the medical realm, expert systems play a role in drug selection, alerting users to potential interactions and proposing alternative medications (MAHINI, 2022).

2.2.3 Natural language understanding

Natural Language Understanding (NLU) is an area of research dedicated to empowering computers to grasp and interpret human language. It entails the development of algorithms and models enabling computers to comprehend, interpret, and generate natural language. NLU finds diverse applications, encompassing tasks like named entity recognition, text classification, sentiment analysis, speech recognition, question-answering systems, and machine translation (QI et al., 2007; OVCHINNIKOVA, 2012). NLU systems aspire to process language in a manner that transcends individual tasks or datasets, fostering a broad understanding of text. Currently, voice-based search demands are the fastest-growing search type.

Along with AI, computers can be programmed to learn, understand, and translate languages (NORVIG, 2012). By employing knowledge-driven semantic representation approaches, NLU systems can genuinely comprehend natural language text and deliver precise responses accompanied by natural language explanations. The utilization of NLU holds the potential to transform human-computer interaction and propel businesses to new heights. In more detail, Natural Language Processing (NLP) can allow computers to identify the ideas or meanings of natural language texts and convey these data in natural language texts. Consequently, NLP performs perfectly for data analytics because it enables the recognition of sentence structure, meaning, and aims via statistical analysis and machine learning processes.

For example, nowadays, NLP has been utilized in security and fraud detection, machine translation, subtitle generation, automated assistants, unstructured data mining, and text semantic comparison (OVCHINNIKOVA, 2012). Also, NLP products can be found in the market, like Amazon’s Alexa, Apple’s Siri, ChatGPT, Google assistant, and IBM’s Watson (KASEMSAP, 2017; STRICKLAND, 2023; PURWANTO et al., 2020). Moreover, AI algorithms can recognize human language and react accordingly. Speech recognition involves converting human speech into text that computer applications can use. Similarly, speech synthesis refers to the generation of human-like speech by computers based on provided text or commands. These technologies have recently been employed in interactive voice response systems, mobile applications, and voice assistants (KASEMSAP, 2017; OVCHINNIKOVA, 2012).

2.2.4 Machine learning and deep learning

Machine learning is regarded as one of the most influential AI tools. It involves the designing, training, and deploying of models to process data, applications, and other machines by providing Application Programming Interfaces (APIs), algorithms, computing power, training and development toolkits (KASEMSAP, 2017). Machine learning plays a vital role in data science, employing statistical techniques to train algorithms for classification, prediction, and uncovering insights in data mining endeavours. Its utility spans diverse sectors, including bioinformatics, intrusion detection, marketing, and image deconvolution (TEJA & REDDY, 2023). The success of AI is attributed to machine learning algorithms, which primarily aim to analyse and learn from data to make decisions and forecast real-world events (CHEN et al., 2016). Consequently, machine learning leverages large amounts of data to train and acquire the ability to perform tasks. Examples include fingerprint recognition, Histograms of Oriented Gradients (HoG)-based object detection, and face detection (LI et al., 2018).

Deep learning, also called deep neural networks, is a machine learning technology that allows computers to learn from experience and understand their surroundings by organizing information into hierarchical concepts (LI et al., 2018). LECUN, et al. (2015) stated that deep learning comprises artificial neural networks (ANNs) with several abstraction layers. Deep learning recognises intricate patterns within large datasets and determines how the machine should adjust its internal parameters using backpropagation algorithms (VERDHAN, 2021). Deep learning is adept at processing unstructured data, such as sounds, texts, images, and videos, making it applicable to a various AI tasks. As data becomes increasingly complex, deep learning is crucial for identifying all possible and relevant information, thereby providing highly intelligent insights. Recently, deep learning has been predominantly employed in applications involving pattern recognition and classification, often supported by extensive datasets (DA XU et al., 2014; KASEMSAP, 2017). Deep learning has found utility across a multitude of domains, encompassing image processing, natural language processing, medical research, computer vision, drug development, customer relationship management, recommendation systems, bioinformatics, predictive analytics, video analysis, virtual assistants, facial recognition, personalization, autonomous vehicles, news aggregation, automatic handwriting generation, colourization of monochrome images, sound addition to silent films deep dreaming, and pixel restoration (MIJWIL et al., 2022). Further, combining deep learning techniques with reinforcement learning enabled AlphaGo to surpass the skills of the best human players.

2.2.5 Robotics

Robotics is an expanding discipline that concentrates on devising machines capable of autonomously perceiving their environment and interacting with one another in the physical realm. It entails the development of systems that can impact human social interactions and find practical applications across various sectors such as manufacturing, automotive, and healthcare (NOLFI et al., 2016; ALSAMHI et al., 2018). Robotic systems provide advantages like heightened output efficiency, enhanced product and service quality, and the capacity to execute complex sequences of tasks. They are deployed in domains requiring repetitive or hazardous activities, augmenting production efficiency and product consistency (FERRER-DÁVALOS, 2023). Robotics amalgamates engineering expertise with cognitive insights encompassing mechanical, electrical, and computer knowledge, representing a continuously evolving field ripe with avenues for exploration. The fusion and compatibility of robotics with other systems, safety considerations, flexibility, adaptability, and autonomy pose notable challenges within the field (FRIGENI, 2022; NOLFI et al., 2016; ALSAMHI et al., 2018).

2.3 Artificial Intelligent Applications

Artificial Intelligence development is rapidly changing our lives. Several countries and companies have established strategic plans to capitalize on the opportunities created by AI. (CAICT & GARTNER, 2018). Over the past few decades, there has been a rise in technology adoption within the business landscape, intending to enhance productivity, reduce costs, save time, and minimize the number of employees. Additionally, it has become crucial for firms to maintain competitiveness, particularly in light of recent trends such as the decline in the prices of robots and the potential rise in labour costs (NOVAKOVA, 2020; ALMEHAIRBI et al., 2022; FERRER-DÁVALOS, 2023). Furthermore, the COVID-19 pandemic crisis forces firms to adopt technology to cope with remote work and the new business environment (MAKARIUS et al., 2020).

The National Science and Technology Council (NSTC) of the United States published the National Artificial Intelligence Research and Development Strategic Plan in 2016. 2017, the US Information Technology Industry Council (ITIC) issued Artificial Intelligence Policy Principles (DUTTON, 2018). In 2019, the U.S. government signed an order for AI Initiative that directs AI development for future investment, formulate international standards for the readiness for the employment crisis, and provides an open government data resource

(DUTTON, 2018). In 2017, the Chinese government unveiled a Next-Generation Artificial Intelligence Development Plan and a Three-Year Action Plan to foster the growth of a new generation-artificial intelligence industry from 2018 to 2020 (DUTTON, 2018). Meanwhile, the U.K. government established the Growing the Artificial Intelligence Industry initiative (HALL & PESENTI, 2017). Also, the Japanese government issued artificial intelligence technology (DUTTON, 2018). In the European Union, the Human Brain Project was introduced in 2013 (MARKRAM, 2012), followed by the Institute of Electrical and Electronics Engineers (IEEE) release of Ethically Aligned Design, Version 2, in 2017 (IEEE, 2017). In 2020, Hungary's innovation and technology minister revealed that the country had formulated its strategy for Artificial Intelligence, focusing on both technical and human sciences aspects arising from AI's development (LÁSZLÓ, 2020). Also, the European Commission released its proposed AI Act in 2021, and it is expected to be the first comprehensive AI law, aiming for finalization in 2024 (YAKIMOVA and OJAMO, 2023). Therefore, the countries and their governments issued policies and regulations to build a convenient work environment for the advancement of AI.

Globally, telecom operators are actively deploying AI technologies (LIANG et al., 2018). In Hungary, the use of AI by current telecom operators is not explicitly mentioned in the provided contexts. However, the telecom industry has significantly adopted AI applications (HUANG et al, 2022). While the specific deployment status in Hungary is not outlined, the telecom sector's historical trend of embracing AI suggests that Hungarian operators are likely exploring or implementing AI solutions to enhance their services and operational efficiency. As seen in other regions, the potential for telecom operators in Hungary to leverage their resources and technology advantages for AI development indicates a promising outlook for AI deployment in the Hungarian telecom sector (VÉRTESY, 2020).

The technological evaluation covers enormous examples, like the Internet of Things, Artificial Intelligence, automation systems, industrial robots, cloud computing, chatbots, digital assistant applications, social robots, IT applications, etc. The major AI applications are associated with big data, NLP, intelligent robots, and visual services (RAJAMANICKAM et al., 2023). AI applications find utility across various sectors, including healthcare, manufacturing, process automation, customer service, tourism, financial services, agriculture, automotive, banking, automated border control, and everyday life (MAKARIUS et al., 2020; CAICT & GARTNER, 2018; PURWANTO et al., 2020; IVANOV et al., 2020). For example, big data-driven AI technologies can potentially to revolutionize financial technology. AI's impact on the current financial landscape will reshape financial services like banking, wealth management, insurance, investment, and lending into more human and intelligent solutions (CAICT & GARTNER, 2018). Many AI approaches, like expert systems, hybrid intelligence systems, and artificial neural networks, have been employed in financial services. These applications involve credit evaluation, financial prediction, planning, and portfolio management (FETHI & PASIOURAS, 2010; CHEN, 2017). MAKARIUS et al. (2020) argued that companies are responsible for fostering socio-technical capital, which entails integrating AI alongside workers in their operations. This integration aims to help employees address their concerns about potential job displacement due to AI implementation. According to HUANG and RUST (2018), their research suggests that companies should contemplate task distribution between AI and employees rather than outright replacement. They advocate for the development of strategies that integrate human-machine services. Further, AI enables robots to possess capabilities resembling those of humans, including perception, feedback, coordination, and decision-making. Intelligent robots are classified into intelligent industrial, service, and specialized intelligent robots (CAICT & GARTNER, 2018). Smart service robots can serve households by providing companionship, assisting in rehabilitating disabled individuals, offering healthcare services, facilitating retail sales, and providing business services. Intelligent industrial robots can handle sorting, positioning, packaging, detection, and assembly tasks. Intelligent specialized robots can perform functions like search operations, reconnaissance, firefighting, and rescue missions (SICILIANO & KHATIB, 2016; NOLFI et al., 2016; ALSAMHI et al., 2018). Moreover, AI has been implemented in education (ZHOU & LAWLESS, 2015), retail (SYAM & SHARMA, 2018), manufacturing (KUSIAK, 2017), smart home (XU et al., 2016), intelligent driving (MEIRING & MYBURGH, 2015), and agriculture (SMITH, 2018). In greater detail, HMOUD and LÁSZLÓ (2019) suggested that integrating AI into human resource management could enhance productivity and outcomes in the recruitment and hiring process. AI could automate time-consuming tasks like candidate sourcing and screening, eliminating human biases. LÁSZLÓ (2020) emphasized the importance of involving customers in decision-making processes to gather feedback on their willingness to engage with intelligent systems in a secure and trustworthy environment. PURWANTO et al. (2020) highlighted the need for digital assistants to provide two-way interactions and ensure privacy protection of users' data, which can help anticipate users' needs. Amazon, Google, and Baidu were the early adopters of AI technology, and they consider technology giants who obtained the most competitive advantage from AI. They provide accurate and reliable results in real-time that may improve customer satisfaction through their application like Alexa and Google Assistant (BRILL et al., 2019). In addition, They are investing in AI to boost their business process, like targeted marketing and optimizing searches. Also, they mainly have been utilizing AI technology like

(ML) machine learning and NLP to issue highly personalized trial for clients. Although AI has enormous applications that can be used in all life and work fields, it is far from the solution to each business problem. Few companies have integrated Al into their processes at a large range. Most companies are still investigating and studying AI adoption and forming plans for AI (CAICT & GARTNER, 2018). In 2023, a significant year in the history of artificial intelligence, we witnessed the emergence of OpenAI's ChatGPT and the introduction of GPT-4, marking notable advancements in AI technology. This period was marked by widespread concerns about the potential negative impacts of AI development, leading to significant events such as the international summit on AI safety and the proposal of groundbreaking regulations like the EU AI Act. Additionally, the year saw the anticipation of the EU AI Act's finalization, expected to become the first comprehensive AI law upon completion in 2024 (STRICKLAND, 2023; YAKIMOVA & OJAMO, 2023).

This study mainly focuses on the following AI applications, considered among the most common AI applications and widely used by businesses:

2.3.1 Customer service chatbots

AI applications find utility in customer relationship management systems, such as deploying chatbots, to automate the handling of customer service queries and guide customers to the appropriate department or staff member. TINTAREV et al. (2016) described chatbots as automated advice providers that can simplify decision-making. According to MAUDLIN (1994), chatbots are implemented as computer programs with natural language capabilities that can be prepared to talk or chat with humans. The chatbot may be found in the form of voice-driven digital assistants like Alexa and Siri. Also, text-based systems like immediate messaging platforms such as Zendesk Answer Bot, ChatGPT, HubSpot Chatbot, IBM Watson Assistant, JetBlue, Amtrak, etc. DOORN et al. (2017) stated that chatbots will smooth customer service and consider them a self-service technology. For example, in immediate messaging platforms, the system can react and communicate with the messages, text, and web pages in customer service channels by utilizing the NLP technology of AI, then analyze and understand the issues' semantics, and finally respond automatically. Chatbots will mainly decrease the workload of customer service agents and enhance customer service efficiency. Therefore, many companies have started to use chatbots in customer service, especially telecommunications companies (CAICT & GARTNER, 2018).

2.3.2 *Speech and voice services for customers*

The automatic speech recognition systems empowered by AI and voice service can be used in a call centre environment, which allows customers to discover or buy products or services by spoken words rather than using remote controls, text-based systems, or even the physical presence (SEHGAL et al., 2018). For instance, Amazon's Alexa pioneered voice services in smart home devices (CHUNG et al., 2017). Semantic speech analysis aids the quality assurance department in promptly identifying sensitive complaint keywords to address customer dissatisfaction and complaints. The substantial volume of customer complaints and inquiries provides valuable feedback. Additionally, combining NLP technology with sentiment analysis enables the detection of customer satisfaction levels, enhancing service quality and optimizing the customer experience (KUMAR, et al., 2016). Another illustration is Djingo, an AI-driven virtual assistant accessible via text or voice commands. Djingo simplifies tasks for customers by facilitating calls, navigating Orange TV, and managing connected home devices (ORANGE, 2018).

Another example is interactive voice response (IVR) systems, and computer-based phone call interaction platforms. They offer functions like call option menus, speech emotion recognition, graphical setup, and gender/accent analysis. IVR systems can process call sequences based on user choices, detect emotions, or filter unwanted calls. They allow real-time configuration changes and convert voice inputs to text for instruction execution and feedback (LU et al., 2021).

2.4 Artificial Intelligence Benefits and Possible Risks

The swift advancements in AI technologies, such as personal assistance, robotics, and sensor technology, will be probable to reshape how individuals, governments, communities, and organizations perceive and interact with them. In the realm of technology innovation, good intentions alone are insufficient. Even well-intentioned technology designs can sometimes yield unintended negative consequences. What once appeared purely fictional just a year ago now appears nearly inevitable. Generative AI systems can already outperform most humans in writing clearly and persuasively, and they can generate art, original images, and computer code based on simple language prompts. This emergence of generative AI represents a significant milestone, marking the onset of a transformative technological revolution that will reshape societies, economies, and politics (KRISHNA, 2024; BREMMER & SULEYMAN, 2022). In the past 3–4 years, new technologies have undergone thorough evaluations in numerous forums, including those at Davos and other international associations like UNESCO. However, as we entered 2023, the swift advancements in AI technologies have sparked sharp and unprecedented criticisms from prominent professionals, institutions, and business leaders. Tesla and SpaceX CEOs have openly expressed concerns regarding the possible hazards associated with artificial intelligence. He emphasizes the necessity for cautious regulation and thorough evaluation of AI's societal ramifications to mitigate potential risks. Despite criticism from various sources, major global corporations like Microsoft, Apple, Amazon, Meta, and Alphabet persist in swiftly progressing their research plans and businesses to capitalize commercially on AI.

In 2022, amidst a tech-led stock market downturn, the major five companies increased their investment in research and development to US$ 223 billion, up from $109 billion in 2019. This amount was in addition to the $161 billion allocated for capital spending, which had doubled over three years (KRISHNA, 2024). The rapid advancements in global AI technology, especially from advanced and industrialized nations, have sparked significant confusion and apprehension regarding the implications of this modern technology. Within its initial six months, ChatGPT has been tried by over a billion individuals. However, the company behind its development has imposed limitations to prevent its misuse. Yet, AI technologies exist from other entities, including governments and companies, that lack such restrictions. Consequently, three distinct perspectives on AI have appeared prominently: 'The Positive Impact,' 'The Negative Impact,' and 'The Alarming' visions. It is beneficial to briefly discuss their impacts on individuals, organizations, and governments (KRISHNA, 2024).

2.4.1 The Positive Impact

Artificial intelligence (AI) applications offer various advantages at the individual level. They offer opportunities for individuals to enhance their public speaking abilities, overcoming challenges such as social anxiety during meetings and stage fear (JADHAV et al., 2023). Additionally, AI facilitates personalized training in engineering education, empowering students to select specialized study areas within the existing curriculum (ADAMOVA & VARLAMOV, 2020). Within education, AI and digitalization play pivotal roles in driving ongoing advancements in the learning journey, guaranteeing prospects for forthcoming generations, and fostering interdisciplinary cooperation (SCHUMANN et al., 2020). Moreover, AI can facilitate engagement through face recognition-based participation and enhance the efficiency of personalized learning experiences (JHA et al., 2023).

Further, HR leaders should prioritize considering how the implemented technologies benefit employees, potentially saving time and fostering motivation for engaging in creative tasks (ODEIBAT, 2021; IVANOV et al., 2020). AI is employed to automate tasks that were once reliant on human involvement, such as decision-making processes and forecasting, resulting in heightened accuracy and effectiveness (JHA et al., 2023). Within the healthcare sector, AI aids in assessing and recommending treatments, diagnosing diseases, and streamlining insurance claim procedures (VARGHESE et al., 2022). Moreover, AI has made significant strides in assistive technologies, benefiting individuals with disabilities and older people by introducing innovative solutions to enhance their quality of life. Overall, AI applications in everyday human life offer tailored experiences, enhanced efficiency, and refined decision-making capabilities.

In summary, utilising of AI applications at the individual level offers several advantages. Firstly, it optimizes time and energy resources by providing efficient access to accurate information. Personal assistants like Siri and Alexa simplify daily tasks, enhancing convenience and productivity. Moreover, AI facilitates easy access to education, knowledge, and information, leading to cost savings and improved learning outcomes. AI-driven robotics and machines contribute to enhanced health outcomes by replacing hazardous tasks with automated processes. For instance, during the COVID-19 pandemic, robotics played a pivotal role in distributing food to patients. Also, AI-driven robotics assists in space exploration and construction activities.

Furthermore, AI applications, such as cleaning robots, enhance comfort and free up time for leisure activities. These technologies also play a crucial role in education, with platforms like ChatGPT and SCISPACE aiding research and information retrieval. In professional settings, AI streamlines tasks such as data analysis, reporting, and project management, boosting efficiency and reducing workload. Additionally, integrating AI in industries like transportation with self-driving cars has the potential to decrease accident rates and road safety.

AI applications within organizations and the economy yield numerous advantages. They can enhance budget management and organizational efficiency, resulting in more effective capital and financial budgeting in evolving environments (WANG, 2022). Companies integrate AI technologies into their operations to gain various advantages, including cost reduction, the development of sustainable automation strategies, enhanced efficiency, time and effort savings, error reduction, reduced strain on human resources, mitigation of human bias, improved strategic outcomes, heightened competitiveness, process automation and bolstered sustainability (DAVENPORT et al., 2020; PASCHEN et al., 2020; MAKARIUS et al., 2020; DAVENPORT & KIRBY, 2015; ODEIBAT, 2021). Iimplementing AI solutions like robotics and automation in manufacturing firms initiates a comprehensive transformational process, customer satisfaction, enhanced productivity, and employee work-life equilibrium. AI advancements promise to reduce expenses, expedite decision-making processes, and accelerate more methodical, data-driven decision-making (BUXMANN et al., 2021). AI's capabilities are showcased across various sectors, spanning medical diagnostics, transportation management, uncrewed vehicles, and environmental sustainability (ALI, HAMDAN & ALAREENI, 2021). Its capacity for autonomous action sets it apart from other organizational technologies, ushering in novel organizational frameworks and questioning established notions of technology within organizational studies (ÖZTÜRK, 2021). Additionally, AI optimizes manufacturing operations by detecting product defects and enhancing delivery routes (KTISTAKIS et al., 2022). AI applications in both organizational and economic contexts promise enhanced performance, efficiency, and decision-making processes.

AI applications in government and policymaking offer numerous benefits. Firstly, AI technology can enhance the effectiveness and efficiency of public sector operations by automating routine tasks, enabling public servants to focus on tasks of higher value (ISAGAH, & BEN DHAOU, 2023). Secondly, AI can contribute to developing better policies and formulating targeted decisions through the analysis of vast datasets, thereby providing valuable insights (ROBLES & MALLINSON, 2023). Moreover, AI has the potential to bolster communication and interaction with citizens and residents, thereby enhancing public services. Additionally, AI holds promise in increasing transparency and accountability in decision-making processes by furnishing interpretable and traceable decision models (OECD and CAF, 2022). AI-based technologies garner growing attention across various research domains encompassing environmental science, sustainability, and climate studies. Instances of this include the utilization of AI in climate and Earth system modelling (RASP, PRITCHARD and GENTINE, 2018), AI-driven environmental monitoring enhancements (HINO, et al., 2018), autonomous underwater interventions for marine conservation and data acquisition (GIRARD and DU PAYRAT, 2017). , AI-facilitated tracking of illegal wildlife trade (DI MININ, et al., 2019), and the implementation of "smart" urban planning strategies aimed at sustainable development (ILIEVA & MCPHEARSON, 2018). Smallholder farmers play a significant role in global food production, particularly in less affluent nations, where many rely on small-scale family farms to fulfil their dietary requirements (LOWDER et al., 2016). Integrating AI with increased automation in agriculture has been proposed to potentially enhance yields and resource efficiency (GALAZ et al., 2021). Integrating AI into government improves decision-making, enhances efficiency, and elevates service delivery standards.

2.4.2 The Negative Impact

The negative effects of AI applications in everyday human life encompass concerns regarding technology displacing jobs across various sectors like commerce, industry, and transportation (PAES et al., 2022). The replacement of human employees by AI systems can result in unemployment and limited job prospects, particularly impacting the younger demographic (AREES, 2023). Adopting AI also prompts apprehensions regarding the possible manipulation of consumers and reliance on smart technologies, potentially influencing an individual's cognitive functions, personality traits, relationships, thought processes, and interpersonal connections (PELAU et al., 2021). Additionally, AI may have limited capabilities in providing social support and empathy to older people, potentially affecting their well-being (BYRNE, 2023). Using AI in services, such as customer interactions, can occasionally lead to customer dissatisfaction and frustration (VARGHESE et al., 2022). Moreover, the technological advancements in AI have contributed to a growing number of unemployed individuals and income inequality, particularly within low-skilled and labour-intensive sectors (ZHAO, 2023). These negative ramifications emphasize the necessity for mitigative measures, including fostering public discourse, enacting legislation and regulations, and considering industrial restructuring and educational reforms.

In conclusion, the pervasive use of AI applications has the potential to significantly affect numerous aspects of our lives, potentially leading to excessive reliance and diminished critical thinking skills. Over-reliance on AI tools may cultivate a sense of dependency, potentially leading individuals to relinquish their ability to think critically and independently, ultimately fostering a culture of passivity. Furthermore, AI's integration into our daily activities could engender a decline in proactive engagement, particularly in tasks related to household chores and personal responsibilities. The convenience offered by AI-driven solutions may inadvertently contribute to a sedentary lifestyle, as individuals may become less inclined to engage in physical activities or routine chores. Moreover, the advent of AI-powered virtual companions, such as virtual boyfriends or girlfriends, can alter the dynamics of social interaction, potentially leading to increased isolation and detachment from real-world relationships. While these virtual entities may offer companionship, they cannot replicate the depth and complexity of human connections, potentially exacerbating feelings of loneliness and social isolation.

Additionally, the widespread adoption of AI technology in various industries poses a significant threat to traditional employment models. With the automation of routine tasks and the emergence of AI-driven solutions, many traditional job roles may become obsolete, leading to widespread displacement in the workforce. Jobs ranging from customer service representatives to delivery drivers, translators, and even actors may be at risk of being replaced by AI-driven alternatives, further exacerbating unemployment rates and economic inequalities. Further, the proliferation of AI-generated content and images raises concerns about the reliability and authenticity of information sources. AI algorithms that generate convincing content may be exploited to manipulate research findings or disseminate false information, undermining the integrity of scholarly pursuits and scientific inquiry.

Furthermore, the inherent biases present in AI algorithms pose a significant challenge to their widespread acceptance and adoption. Instances of algorithmic bias, where AI systems perpetuate or amplify existing societal prejudices, can erode trust in AI applications and decrease customer satisfaction. Addressing these biases and ensuring AI technology’s ethical development and deployment is paramount to fostering trust and confidence in AI-driven solutions.

The negative effects of AI applications within organizational and economic realms encompass various concerns, including skill obsolescence, heightened autonomy of digital systems, job displacement, exacerbated inequality, augmented potential for employee surveillance, diminished wages, and a shrinking tax base (SHARMA & BIROS, 2021). AI's implementation carries the risk of detrimental consequences across social, financial, and legal domains, potentially fostering the emergence of mega-corporations that pose systemic risks to the economy. Furthermore, AI-driven decision-making processes can impact significant segments of the populace, often ensnaring vulnerable societal groups (SOOD, 2021). The expansion of AI has the potential to reshape the current employment landscape, necessitating retraining initiatives for the workforce (NOVICHKOV et al., 2020). A questionnaire from DELOITTE (2017) revealed that 47% of senior managers overseeing 152 AI projects encountered difficulties integrating AI technologies with existing staff, systems, structures, and processes (ODEIBAT, 2021). Besides, adopting AI may induce technostress among workers, manifesting as concerns regarding information security, data privacy, significant changes stemming from digital transformations, and apprehension about job stability and security. In various industries, resource limitations and uneven availability of information and communication technologies (SALEMINK et al., 2017) pose additional challenges as AI technologies permeate new sectors. This trend is evident in the increasing focus on digital, data-centric, or precision farming. However, even conventional agricultural technologies designed to enhance productivity are often considered financially out of reach for individuals in impoverished local communities (JIREN et al., 2020). Furthermore, a notable "digital gap" exists in data-driven agriculture, with small-scale farmers encountering significant barriers in accessing extensive data and mobile technologies. This inequality in access will likely result in disparate distribution of the benefits derived from these technologies (GALAZ et al., 2021; MEHRABI et al., 2021).

The negative effects of AI implementations in governmental and policy contexts extend to the phenomenon known as algorithmic transference, where algorithmic failures are generalized more widely than human failures (LONGONI et al., 2022). This transference occurs because AI systems are perceived as more uniform than humans, resulting in a higher failure rate in information transfer between AI algorithms than between individuals (TABARES-SOTO et al., 2022). The premature or mishandled deployment of flawed AI technologies can undermine the institutions they are intended to modernize, potentially impacting consumers and societies negatively (MISRA et al., 2020). Furthermore, challenges related to AI adoption in the public sector, such as exclusion and bias, necessitate implementing regulatory public policies to mitigate adverse effects. Additionally, to address the governance of AI risks for sustainability, a balance between strict and adaptable governance modes is required (BRASS & SOWELL, 2021). These governance strategies must be capable of responding to evolutions in ecological systems, climate systems, and advancements in AI technologies simultaneously. Such approaches should involve private entities, governmental, self-regulatory, and mandatory interventions to ensure flexible and polycentric responses. Governments, investors, and the private sector must take these matters seriously, as AI-augmented technologies are increasingly touted as essential solutions for addressing the challenges of a volatile climate future (GALAZ et al., 2021).

2.4.3 The Alarming

While AI applications offer numerous advantages and disadvantages, it is essential to acknowledge that they also pose potential risks. Beyond their negative aspects, AI technologies can evoke concerns, and the following discussion outlines some of these potential risks. Artificial Intelligence holds potential for military applications, encompassing defensive and offensive roles. Its utilization within the military sector introduces ethical, legal, and concerning implications. Specifically, AI-driven autonomous weaponry, also known as lethal autonomous weapons systems (LAWS), can identify and engage targets without human intervention. This gives rise to apprehensions regarding AI's capability to make critical life-or-death decisions, the possibility of unintended consequences, and ethical dilemmas.

Moreover, AI can facilitate the development of sophisticated cyber warfare tactics. AI-enabled malware and cyber weapons can exploit vulnerabilities within computer systems, whereas AI-powered cybersecurity solutions can identify and neutralize threats (KRISHNA, 2024). As per a statement from FORTUNE, the U.S. military is escalating its dedication to developing and deploying autonomous weaponry, as indicated by a Department of Defence directive issued on

January 25, 2023 (DAWES, 2023). Additionally, a Time report highlights the ongoing conflict between China and the U.S. regarding the use of killer robots and the future trajectory of AI (MELISSA, 2019). The militarization of AI technologies by rogue nations and non-state entities poses a significant threat to global safety and cyber warfare. These entities are leveraging artificial intelligence capabilities for various offensive purposes. The following are examples of how AI is being weaponized:

Malicious Software and Code: AI can assist in creating sophisticated malware capable of adapting to defensive measures and avoiding detection, including polymorphic malware that constantly alters its code to evade signature-based detection methods.

Cyberattacks and Hacking: AI may be utilized to design more intricate and compelling cyberattack devices, streamlining tasks such as surveillance, vulnerability scanning, and malware distribution, thereby increasing the precision and impact of cyberattacks.

Deceptive Tactics and Social Manipulation: AI can analyse extensive datasets to craft compelling phishing messages and emails, facilitating the deception of individuals and gaining unauthorized access to sensitive systems or information.

Deepfakes: AI-generated deep-fake audio recordings and videos can mimic individuals, including public figures, to disseminate false information or propaganda, potentially leading to significant social and political ramifications.

Automated Botnets: AI-powered botnets can orchestrate distributed spam campaigns, denial-of-service (DDoS) attacks, and online manipulation tactics, resulting in widespread and coordinated disruption.

Data Manipulation: AI can be deployed to tamper with data, modifying knowledge within databases or financial records to generate financial harm or confusion.

Biometric Deception: AI technologies can generate authentic-looking biometric data, like facial features or fingerprints, to evade biometric safety measures.

Espionage and Intelligence: AI systems can be employed for automated data analysis, gathering, and espionage operations, providing valuable insights into adversaries' actions.

Autonomous Cyber Warfare: The emergence of autonomous cyber weapons capable of independent decision-making and adaptation without human interference is a growing fear in cybersecurity.

Fabricated Identities and Social Engineering: Adversarial actors may leverage AI-powered social engineering techniques and chatbots to form fake online personas or influence public views on social media platforms.

The militarization of artificial intelligence complicates attribution (identifying the perpetrators of attacks), response (developing effective countermeasures), and policy formulation. Security professionals, policymakers, and entities are working to address these evolving threats and mitigate their impact on global security (KRISHNA, 2024).

2.5 The theoretical framework for AI adoption

This section will discuss the previous literature regarding the theoretical framework for information technology (IT) adoption , a benchmark for AI utilizations, and the most relevant models. It will include three parts: the first will cover the literature on information technology adoption, the second will address IT adoption theories and models, and the last will focus on the theoretical framework for artificial intelligence adoption.

2.5.1 The literature on Information Technology (IT) adoption

Adopting modern technology is an effective strategy for achieving business success (SCHWAB, 2017; GEFEN and STRAUB, 2000). Previous literature has explored the adoption of IT innovations or new systems at both organizational and individual levels (OLIVEIRA & MARTINS, 2011). Concerning individual behaviour in accepting technology, the Theory of Reasoned Action (TRA) elucidates how individuals respond based on their attitudes and norms (FISHBEIN & AJZEN, 1975). Further, AJZEN (1991) supported the Theory of Reasoned Action (TRA) in his studies and proposed the Theory of Planned Behavior (TPB), which suggests that subjective behavior, norms, and perceived behavioural control collectively influence an individual's behavioural intentions and actions. DAVIS (1985) introduced the Technology Acceptance Model (TAM) based on TRA to examine factors contributing to the rejection or acceptance of IT. The TAM illustrates that various factors influence users' decisions regarding new technology and their subsequent application of it (DAVIS, 1989). Research has validated the Technology Acceptance Model (TAM) and confirmed the relationship between actual system use and behavioural intent (MOHAMMADI, 2015; WALLACE & SHEETZ, 2014; VENKATESH et al., 2003). However, the TAM does not cover some social impacts and the quality aspect of an IS. Therefore, a new theory the Unified Theory of Acceptance and Use of Technology (UTAUT) has been proposed, illustrating users' intent to apply IT systems and their subsequent usage behaviour (VENKATESH et al., 2003). UTAUT attempted to understand the relationship between actual usage behaviour and predictive users' behaviour (VENKATESH et al., 2003; DWIVEDI et al., 2017). Subsequently, UTAUT has been extensively employed in IT adoption studies across various contexts. Yet, many studies utilizing UTAUT have identified certain limitations. For example, some mediators assume specific research settings that may not always be available, and a significant proportion of these mediators were discarded (VENKATESH et al., 2012). Additionally, it has been claimed that the relationships between research constructs lack inclusiveness (VENKATESH et al., 2016; DWIVEDI et al., 2017). However, to enhance its explanatory power and validity, VENKATESH et al. (2012) developed UTAUT 2, which extends the original model by incorporating additional variables while excluding some mediating variables.

At the organizational level, the Technology-Organization-Environment (TOE) framework was introduced to explore how environmental factors and technological influence firms' decisions regarding adopting technological innovations (TORNATZKY & FLEISCHER, 1990). TOE has redirected focus from subjective factors to multifaceted functional ones adaptable to diverse contexts with fewer limitations. Moreover, it offers a comprehensive method to evaluate the factors affecting decisions on adopting IT innovations and opportunities for development (LIN & LIN, 2008; GANGWAR et al., 2014; PAN & JANG, 2008). The technological context encompasses internal and external technological factors at both organizational and individual levels. It involves evaluating the attributes of the innovation against the technological characteristics of the adopting organization to determine the overall technological compatibility. This procedure allows the adopters to identify the benefits the organization may gain from adopting the examined IT innovation (OLIVEIRA & MARTINS, 2011; AL-DMOUR, 2014). Conversely, it also evaluates the presented technological factors that may impede or facilitate the adoption of IT innovation (CAO et al., 2014; TROSHANI et al., 2011). The organizational context pertains to the actual characteristics, structure, and processes within the organization that may either delay or facilitate the implementation of the IT revolution (CAO, et al., 2014). Several scholars researched the factors influencing companies' IT adoption based on the TOE framework. For example, a survey aimed at exploring the uses of Quality Function Deployment (QFD) in the U.S. and Japan that included more than 400 firms found that organizational characteristics, like data sources, management support, and motivation, positively impacted the successful utilization of QFD (CRISTIANO et al., 2001). Another four factors identified from a qualitative study by QUADDUS and XU (2005) impact the diffusion and adoption of Knowledge Management Systems (KMS) in firms, as follows: managerial support, organizational culture, benefits to individuals, and the vision of knowledge management systems (KMS). KOSAROGLU and HUNT (2009) claimed that administrative skills, leadership, and technical and managerial factors grant the success of new product development (NPD) schemes. Moreover, from analysing 27 management variables connected with human factors that impact organizations' implementation of advanced manufacturing technology (AMT) such as institutional changes and external consultants, team structure, vendor participation and sustainability, education, leadership, manufacturing strategy and the impact of technology, and other factors, they found many benefits like improvement of product quality, reduction in labour cost, improvement in productivity, and provision of competitive benefit in marketing (CO et al., 1998). In addition, OLIVEIRA and MARTINS (2011) analysed the IT adoption study models at the organizational level, comprising diffusion of innovation (DOI) theory (ROGERS, 1995), TOE framework (TORNATZKY & FLEISCHER, 1990), electronic data interchange (EDI) framework (IACOVOU et al., 1995), and institutional theory (SCOTT & CHRISTENSEN, 1995).

2.5.2 The theories and models of Information Technology (IT) adoption

As shown in previous literature, IT adoption studies have extensively used UTAUT, TAM, and TPB. Despite this, they are valid for individual-level research. At the organizational level, the DOI and the TOE framework are the two most commonly employed theories in IT adoption studies (OLIVEIRA & MARTINS, 2011; CHONG et al., 2009; CAO et al., 2014; TROSHANI et al., 2011). ROGERS (1995) described the DOI Theory as a historical social science theory originating from communication. It seeks to explain how product or idea gains traction and disseminates throughout a social system or particular population over time. He elaborated that diffusion involves the gradual spread of innovation among participants and within social systems. DOI theory states that innovations must be widely adopted to achieve sustainability and development.

According to HIDAYAT and MUKMININ (2022), the DOI Theory elucidates how concepts, new ideas, technologies, and methodologies disseminate across systems or cultures. Its emphasis lies in comprehending the reasons and mechanisms behind the adoption of innovations by groups or individuals. ROGERS (2003) suggested that individuals who embrace an innovation in its early stages exhibit different traits than those who adopt it later. Furthermore, he categorized adopters into early adopters, innovators, majority, early majority, and laggards. Also, the strategies for each adopter type must be different when introducing innovation. Innovation is a communication process that utilizes various channels within the social system (ROGERS, 2003). Three factors affect innovation adoption in organizations. The first factor is the individuals, which reflects the leadership's attitude toward change. The second factor indicates the internal organizational structure, including complexity, centralization, interconnectedness, organizational slack, and the number of employees. The last factor is the external characteristics of the organization (ROGERS, 2003; OLIVEIRA et al., 2014;). The DOI process is affected by four factors: social system, communication channels, time, and innovation characteristics. DOI depends on innovation characteristics such as compatibility, complexity, relative advantage, trialability, and observability (OLIVEIRA & MARTINS, 2011; ROGERS, 1995), and these elements have various levels of influence on the adopter types. It confirms that organizational and individual characteristics are the drivers of organizational innovation. In addition to Rogers' factors, BUTLER and SELLBOM (2002) pointed out that the features of the innovation itself, as well as numerous psychological, economic, organizational, and sociological variables, influence the adoption and diffusion of innovation in firms.

The TOE is a comprehensive research framework that examines the factors influencing the adoption and implementation of technology-based solutions in various contexts. It considers the environmental, technological, and organizational factors that impact the adoption and success of these solutions. ALIGARH, et al. (2023). The TOE was issued by TORNATZKY and FLEISHER (1990), which indicates the factors that affect technology adoption. The TOE mainly involves three approaches to the organizational factors that impact the process of technological innovation: environmental context, technological context, and organizational context. The environmental context refers to the regulatory environment, the competitors, and the market elements. In greater detail, the environmental context pertains to the overall conditions and surroundings in which an organization operates, with a particular focus on external factors like government regulations, competition, and industry dynamics. It is claimed that environmental factors are the most important within the various contexts and can either facilitate or hinder the adoption of IT innovation (TROSHANI et al., 2011; OLIVEIRA & MARTINS, 2011). For example, industries experiencing rapid growth and change tend to be more inclined toward innovation and may present heightened competition for organizational innovations (TORNATZKY et al., 1990). Additionally, dynamic global policies, such as those concerning climate change and governmental regulations, can influence the acceptance of innovations. Furthermore, unforeseen circumstances like the COVID-19 pandemic have played a pivotal role in compelling organizations to seek and embrace IT innovations that facilitate remote work, distance learning, and virtual interaction. For instance, in the COVID-19 pandemic, workers have been divided into three groups the first one is "essential workers" like health employees and shop assistants; the second "remote workers" like teachers and customer service representatives; and the last one "displaced workers" such as Hospitality and Tourism, travel employees. All three worker categories needed reskilling, more flexibility, and an upskilling agenda (Schwab & Zahidi, 2020). Consequently, uniting leaders' and employees' efforts to powerfully build a Socio-Technical work environment by integrating Al in efficient socialization will achieve growth alongside machines, not against them. The context of technology covers the external and internal technologies that relate to the company. The assessed attributes of innovation are compared with the technological features of the adopting organization to gauge the overall compatibility. This procedure allows adopters to understand the potential benefits the organization may gain from embracing the investigated IT technology (OLIVEIRA & MARTINS, 2011; AL-DMOUR, 2014). Conversely, it also evaluates the existing technological characteristics to determine whether they aid or impede the adoption of IT innovation (CAO et al., 2014; TROSHANI et al., 2011).

The organisational context includes the resources and the company's characteristics. This pertains to an organization’s actual attributes, structure, and operations, which can either hinder or facilitate the adoption of IT innovation (CAO et al., 2014). For example, studies have examined factors such as management backing, communication channels, size, culture, supportive conditions, human resources, and other key indicators of organizational adaptability (GANGWAR et al., 2014). Therefore, the TOE is regarded as a comprehensive perspective for investigating the adoption of IT technology within organizations (YANG et al., 2013). It enhances the DOI theory's capacity to elucidate the diffusion of innovation within firms (HSU et al., 2006). Moreover, it is applicable across companies of varying sizes and industries (WEN & CHEN, 2010). While the exact factors delineated among the three contexts may differ among research, TOE has consistently served as a significant contextual framework for determining the adoption of IT at the organizational level (OLIVEIRA & MARTINS, 2011; BAKER, 2012). Numerous studies examine the success factors impacting IT adoption based on the TOE (ZHU et al., 2003; KUAN & CHAU, 2001).

2.5.3 The theoretical framework for Artificial Intelligence (AI) adoption

The theoretical framework for adopting Artificial Intelligence (AI) involves evaluating AI's suitability for traditional industries based on practical and contextual values. Additionally, the framework considers the role of service reliability as a moderator influencing AI acceptance and its consistent integration into routine operations within traditional industries (KHAN, 2023). In software engineering, the adoption of AI tools is primarily influenced by their compatibility with existing development workflows, which deviates from conventional theories of technology acceptance (RUSSO, 2023). A conceptual framework is necessary to streamline terminology across disciplines and establish appropriate metrics, standards, and mechanisms for institutional AI research and adoption. Within the education sector, a systematic process is recommended for effectively adopting AI technology, highlighting the significance of technological transformation within organizations (STRAUB et al., 2023; KHAN, 2023).

Moreover, some research has studied AI technologies employed in specific areas (e.g., SIMOU et al.,, 2013; LI et al., 2017). Other research investigates the theoretical foundation of AI (ZOU, 2015; MURPHY, 2018) and its applications (QIU, 2018; KOUZIOKAS, 2017). However, limited studies examine AI adoption, especially at the organizational level. For instance, ALSHEIBANI et al., (2018) issued a research framework for AI adoption. Nevertheless, the framework lacks validation across organizations to detect the factors that influencing AI adoption.

Additionally, empirical validation and hypothesis tests are missing in their research. Various research studies have been conducted on AI applications, such as expert systems (COATS, 1991) and decision support systems (STEIGER,1998; LEE,1988). Few studies test AI technologies or applications (ALEKSANDER, 2017; SUN YIN et al., 2019; FOWLER, 2000). The lack of studies on AI adoption at the organizational level and the ubiquitous nature of AI prevent the direct development of existing theories. AI adoption at the organizational level is a complex procedure that involves various factors and challenges. It is a complicated task that needs not only the purchase of hardware and software but also suitable resources and infrastructure for an extended period. There are limited studies investigating AI adoption. Therefore, studies should consider the factors that influence the tendency toward AI adoption and the environmental circumstances, and exact organizational capability of an organization. International institutions play a vital role in shaping the norms and governance of AI (CHINEN, 2023). Integrating AI into organizations can result in enhanced business insights, streamlined IT systems, and innovative solutions, although many organizations face difficulties realizing these advantages (ODEIBAT, 2023; NOVAKOVA, 2020). The adoption of AI within organizations is influenced by task interdependencies and the necessity for comprehensive system changes (AGRAWAL et al., 2023). Organizations must embrace AI technologies to remain competitive in innovation, and the normalization of AI readiness can align with existing digitization models (ODEIBAT, 2023; NOVAKOVA, 2020). Obstacles to AI adoption in organizations include insufficient regulations and inadequate IT infrastructure, necessitating government attention to enhance adoption (CHINEN, 2023). Overall, comprehending the obstacles and opportunities associated with AI adoption at the organizational level is essential for successful implementation and utilization.

The examination of research on AI adoption indicates that the TOE offers a solid foundation for studying AI adoption. This is because it identifies the specific in which the adoption occurs and allows for the assessment of factors influencing AI adoption. Therefore, this research opts to utilize the TOE as its theoretical basis. In addition, the DOI theory has been adopted to investigate AI adoption. Furthermore, researchers have combined the DOI and TOE to study IT adoption (OLIVEIRA and MARTINS, 2011) and AI adoption (CHEN, 2019). The current research uses this strategy to investigate the adoption of AI. In Table 1, the previous literature about the TOE framework in three different contexts is presented: the environmental context, the organizational context, and the technological context.

Table 1.The Technology-Organization-Environment (TOE) framework contexts

The technological context	The organizational context	The environmental context
The characteristics of technological advancement, technical proficiency, and range of technologies available (ROGERS, 2003; YANG et al., 2013).	The characteristics include culture, strategies, managerial skills, technical skills, and personnel factors (TEECE, PISANO and SHUEN, 1997; YANG et al., 2013).	The environmental context comprises the competitive landscape, legal and regulatory framework, and market conditions within which firms operate (YANG et al., 2013).
ROGERS (1995) argues that the diffusion of a new technology depends on some innovation characteristics of this technology, such as relative advantage, compatibility, complexity, trialability, and observability.	Organizational factors include the structure and processes of the organization, limiting or promoting the adoption and implementation of innovations (CHAU and TAM, 1997).	ETTLIE (1983) points out that the greater the competition between companies, the more likely the adoption of innovation. Heightened competition can accelerate the swift dissemination of innovations, prompting companies to adopt assertive technology strategies when faced with considerable market uncertainties (CHAU and TAM, 1997).
When relative advantage, compatibility, trialability, and observability of a new technology increase, the rate of its adoption rises (ROGERS, 1995).	RAYMOND (1990) notes that organizational size, maturity, resources, time frame, and IS sophistication are related to information system success.	CHANG ET AL. (2006) finds that government involvement through policies and support can influence firms' decision of new systems adoption to a large extent.
Other than innovation characteristics, three technological factors, including relative advantage, compatibility, and complexity, are found to affect IT adoption (CHONG et al., 2009; THONG, 1999; ZHU et al., 2006).	Other organizational factors are founded to play a role in IT adoption, including formalization of system development and management (CHAU and TAM,1997), IT training program (OLIVEIRA and MARTINS, 2008), management level for information (LIU, 2008), firm size (LIU, 2008; ZHU et al., 2003), organizational compatibility (LIN and LIN, 2008) and managerial support (TEO et al., 2006)	Other environmental drivers are identified by previous studies as well, including government involvement (CHANG et al., 2006), regulatory policy (PAN and JANG, 2008), industry pressure (KUAN and CHAU, 2001), market uncertainly (CHAU and TAM, 1997; TEO et al., 2006), and competitive pressure (OLIVEIRA and MARTINS, 2008; PAN and JANG, 2008; ZHU and KRAEMER, 2005).

Source: Constructed by author

3. RESEARCH MODEL AND HYPOTHESES DEVELOPMENT

In chapter two, the review delved into research and relevant literature addressing the phenomena of IT and AI adoption, all aimed at fulfilling the research objectives. Variations were observed in the environmental, organizational, and conceptual contexts across the reviewed literature. Furthermore, it became evident that the evolution of technology adoption research and theory perspectives on the significance of adoption factors closely correlated with technological advancements over the years. The literature review highlighted a gap in understanding regarding the validation of factors influencing organizations' adoption of AI and their interconnectedness in shaping adoption decisions. Consequently, the research focus shifted between initially concentrating on business processes and inner dynamics, to the emergence of the internet and eventually, the influence of external factors and individual perceptions. The overarching aim was to enhance comprehension of the study topic and create a strong conceptual framework to guide investigation efforts toward meeting the research purposes. Hence, this research delves into examinating the research model, merging the TOE and DOI to delve deeper into the determinants of AI utilization success within organizations. Additionally, the conceptual framework offers a holistic perspective, linking the factors postulated to be associated with managerial capability in AI adoption. The examined factors can be categorized into the following three primary constructs:

1. Technology-Organization-Environment (TOE)
2. Attributes of AI innovation
3. Managerial capability

In particular, this research categorized the influencing factors into three main aspects: external environmental influences, the attributes of AI innovation, and organizational capabilities. The factors considered within the attributes of AI innovation include complexity, relative advantage, and compatibility. Under organizational capability, emphasis is placed on technical capability and managerial support. Furthermore, external environmental factors encompass competitive pressures, government involvement, vendor partnerships and market uncertainty. This classification is illustrated in Table 2. The selection of study constructs is based on their significant influence on AI adoption at the organizational level. The proposed research model, illustrated below (Figure 3), aims to comprehend and explore the anticipated relationships among research factors and their impact on firms' decisions to adopt AI technologies. It is anticipated that this model will effectively address the study goals. Grounded in established theoretical frameworks, this conceptual model draws upon previously validated theories of IT innovation diffusion. It is worth noting that all of the variables determined in this research are from existing literature and have previously been used to explain well-known research on the diffusion of IT technology. Nevertheless, their relative importance may vary across different research contexts, as indicated by previous studies.

Table 2.The factors that affect AI adoption at the organizational level

Innovation attribute of AI	Organaizational capabilty	External environment
Complexity	Technical capability	Government involvement
Compatibility	Managerial support	Market uncertainty
Relative advantage		Competitive pressure
		Vendor partnership

Soucre: Constructed by author

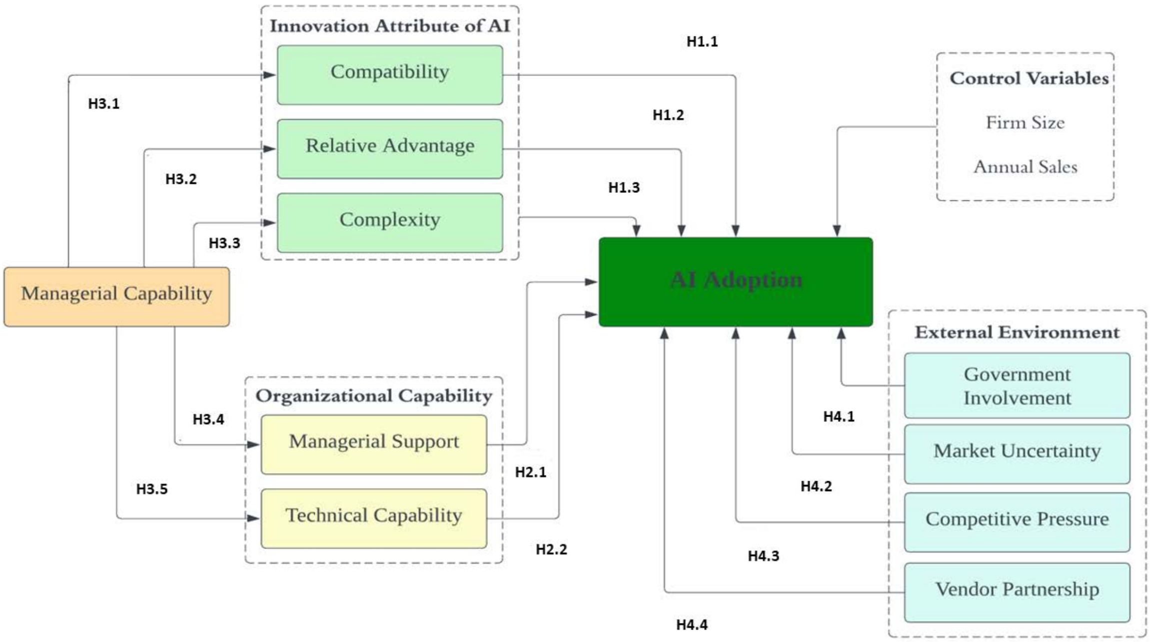

Figure 3. Research Model for Artificial Intelligence Adoption

Source: Build based on (TOE) framework and DOI theory (CHEN, 2019).

3.1 Innovation attributes of AI

Innovation characteristics of AI elucidate the fundamental factors influencing the adoption of AI from the context of a technological perspective. The literature has extensively investigated these innovation attributes and their impact on the innovation process. Although Rogers (1995) identified five innovation qualities in the Diffusion of Innovation theory (DOI), specifically complexity, relative advantage, compatibility, observability, and trialability, just the first three are reliably linked to innovation adoption at the organizational level in previous studies (WU et al., 2007; TORNATZKY & FLEISCHER, 1990; KWON & ZMUD 1987; CHAU & TAM,1997). Table 3 presents the hypothesis development, proposing a set of hypotheses that illustrating the predicted relationships between the variables.

Table 3. The hypothesis development

Innovation attribute of AI	AI adoption	Managerial capability
compatibility	H1.1: Compatibility is significantly associated with AI adoption.	H3.1: Managerial capabilities affect the compatibility of AI positively.
relative advantage	H1.2: Relative advantage is significantly associated with AI adoption.	H3.2: Managerial capabilities positively affect the relative advantage of AI.
complexity	H1.3: Complexity affects AI adoption negatively.	H3.3: Managerial capabilities affect the complexity of AI negatively.
Organizational capability	**AI adoption**	**Managerial capability**
Managerial support	H2.1: Managerial support influences AI adoption positively.	H3.4: Managerial capabilities influence the managerial support positively.
Technical capability	H2.2: Technical capabilities positively affect to AI adoption.	H3.5: Managerial capabilities are positively associated to technical capabilities.
External environment	**AI adoption**	
Government involvement	H4.1: Government involvement is positively associated with AI adoption.	
Market uncertainty	H4.2: Competitive pressure is positively influencing AI adoption.	
Competitive pressure	H4.3: Market uncertainty is negatively associated with AI adoption.	
Vendor partnership	H4.4: Vendor partnership is positively associated with AI adoption.	

Source: Constructed by author

3.1.1 Compatibility

Compatibility indicates the innovation's capability to give value and experience while remaining compatible with the requirements of the possible adopters (ROGERS, 2003; ROGERS, 1995). Further, he highlighted compatibility as one of the five primary innovation attributes influencing its spread. Consequently, it has been underscored as a significant element affecting adopter perceptions when evaluating workplace automation. Therefore, compatibility emerges as a crucial aspect of adopting innovation (AZADEGAN & TEICH, 2010; OLIVEIRA et al., 2014; CHONG & BAUER, 2000). According to the DOI theory, the compatibility between innovation, user requirements, and experiences correlates positively with adoption rates. A heightened level of compatibility can lead to improved adoption outcomes. Although the integration of AI into businesses holds the promise of significant advancement and may be perceived as technically proficient in task execution, its adoption may face obstacles if potential adopters perceive it as inconsistent with the recent socio-cultural values and beliefs, practices, or needs.

Furthermore, ROGERS (2003) identified two dimensions of compatibility: the practices and the values of the adopter. The literature reveals various dimensions researchers explore when assessing the innovation’s compatibility. For illustration, TORNATZKY and KLEIN (1982) discoursed normative compatibility, focusing on norms and values, as well as operational compatibility, which pertains to aligning current practices with proposed innovations or technologies. PREMKUMAR and RAMAMURTHY (1995) emphasized compatibility with existing hardware/software, termed technical compatibility, while also considering practices and values as organizational compatibility (WANG et al., 2016). Furthermore, compatibility involves ensuring that the firm's technological strategies align effectively, such as considering the cost of technology when implementing AI applications (AL-DMOUR, 2014). Studies (GRANDON & PEARSON, 2004; LIN & CHEN, 2012; TEO et al., 2007) have demonstrated that strong compatibility is a crucial factor distinguishing non-adopters from adopters and has been recognized as a catalyst for the adoption decision. For example, research by YANG et al. (2015) revealed the substantial influence of compatibility on the adoption of software-as-a-service (SaaS). Furthermore, investigations (DAS & DAYAL, 2016; A. LIN & CHEN, 2012) have indicated that compatibility significantly enhances user attitudes toward adopting cloud-computing technology. Higher compatibility leads to swifter adoption (WU et al., 2007). When AI technology aligns with current work practices, organizations require fewer adjustments, and employees are more inclined to use it. Conversely, incompatible technologies often necessitate substantial process changes, which entail extensive learning curves and foster resistance to adoption. AI, particularly machine learning, relies on vast amounts of data (HUANG et al., 2006), so integrating AI with existing data resources becomes feasible for companies. Additionally, if AI aligns with current IT infrastructures, implementation costs and timeframes are reduced, thus facilitating adoption. Consequently, the following hypothesis arises.

H1.1: Compatibility is significantly associated with AI adoption.

3.1.2 Relative advantage

The relative advantage is the degree to which an innovation is superior to the approach it replaces (YANG et al., 2013). According to ROGERS (2003), the potential value of innovation influences a firm's decision to adopt innovative technology. Consequently, recent technologies that deliver clear and precise advantages in increasing operational and strategic efficiency have more potential to be adopted. In simple terms, the more significant the apparent relative advantage of innovative technology, the more quickly it will be adopted (GREENHALGH et al., 2004). When potential adopters perceive that a particular innovation offers more significant advantages in meeting their needs, its adoption tends to occur more rapidly than other options. The factors influencing relative advantage vary depending on the innovation nature, including economic gains, social benefits, security considerations, increased convenience, time savings, facilitation of decision-making processes, or overall improvements in effectiveness and efficiency (ROGERS, 2003; LIN & CHEN, 2012).

Conversely, to assess the relative advantage of an innovation, potential adopters need to acquire knowledge and understanding of its qualities, either through theoretical learning, observing competitors, or gaining practical experience. TORNATZKY and KLEIN (1982) recognized relative advantage, compatibility, and complexity as the primary attributes of innovation consistently associated with adoption. Additionally, previous studies (TORNATZKY et al., 1990; RAMAMURTHY & PREMKUMAR, 1995) have consistently found that relative advantage is one of the strongest predictors that positively influence the adoption of innovations. Furthermore, research on IT adoption (PREMKUMAR & ROBERTS, 1999; OLIVEIRA et al., 2014) has extensively explored the relationship between user-perceived relative advantage and IT adoption. These studies have consistently shown that the relative advantage of an IT innovation is a highly reliable predictor in IT adoption research, observed in both early and contemporary studies on emerging IT adoption trends.

To summarise, a more significant relative advantage of new technology results in heightened adoption. Given the fierce market competition and swift shifts in the business landscape, organizations feel compelled to embrace state-of-the-art information technologies to enhance their operations. AI possesses robust capabilities in computing, cross-border integration, and deep learning (RUSSELL & NORVIG, 2016), offering the potential for widespread deployment of further services. Integrating AI applications with vast data is expected will generate competitive advantages and foster businesses innovation. AI has already been applied in various areas, such as speech and voice services for customers and customer service chatbots (EL KHATIB et al., 2019), resulting in reduced operational costs, enhanced customer experiences, improved service quality, and increased efficiency for companies. By increasing workers' awareness of core AI technologies like deep learning and NLP through training or education, companies can help employees better understand AI's benefits. As awareness levels rise, individuals may be more inclined to accept and actively engage in the positive changes facilitated by AI. Therefore, the following hypothesis is proposed:

H1.2: Relative advantage is significantly associated with AI adoption.

3.1.3 Complexity

Complexity is the level to which an innovation is recognized as tough to comprehend, realize, and use. Also, complexity represents the obstacles to AI adoption (YANG et al., 2013). It denotes the challenges or hindrances to the adoption of AI. The simpler it is to implement technology into operational processes, the more likely it will be adopted (OLIVEIRA et al., 2014). Complexity is a key attribute of the DOI and is consistently acknowledged for its impact on adopting innovation. ROGERS (2003) defines complexity as the degree to which an innovation is perceived as challenging to understand and apply, reflecting users' perceptions of the innovation at hand. The intricacy of AI lies in its immaturity, scarcity of IT specialists, technological expertise, time-intensive nature, and high expenses.

The attributes of AI illustrate that its immaturity represents the most significant barrier to its adoption. Moreover, GOPALAKRISHNAN and DAMANPOUR (1994) have contended that complexity encompasses several aspects. Initially, it involves the degree of divisibility of the innovation and its applicability on a limited scale, where more divisibility indicates less complexity. Secondly, it pertains to the intellectual challenge associated with learning innovation. The more sophisticated and novel the knowledge base, the greater the complexity of innovation.

To conclude, complexity indicates the novelty and uniqueness of the innovation; the more recent and distinctive the innovation, the greater the perceived complexity by possible users (GOPALAKRISHNAN & DAMANPOUR, 1994). Previous research suggests that the degree of IT maturity plays a significant role in shaping companies' strategic choices concerning adopting and deploying IT solutions. When modern technology is well-established, organizations have a clearer understanding of how to implement it effectively. Also, if they could establish effective collaboration with vendors, organizations would be more ready to adopt the technology (HUANG & PALVIA, 2001). Furthermore, increased perceived complexity may raise concerns about the associated risks of adoption.

Additionally, complexity may arise from users' lack of skills, knowledge, and capacity to fully grasp the complexities of an IT innovation, thereby leading to more excellent resistance (AL-DMOUR, 2014). Another challenge hindering AI implementation is the absence of proficiency in data analysis and AI software. According to ATTEWELL (1992), another impediment to AI adoption is a scarcity of AI software and data analysis expertise. Firms delay the internal implementation of complicated technology till they've gained enough technical expertise to implement and operate it successfully. Complexity has been demonstrated through empirical research to be a significant aspect in studies of IT adoption. This has been evidenced in business intelligence (ROUHANI et al., 2018) and cloud computing (PALOS-SANCHEZ et al., 2017). Despite this, many companies are still unfamiliar with AI technologies, lacking a comprehensive understanding of their intricacies. Given the ongoing evolution and development of AI technologies, further investigation is warranted to comprehend the reasons behind this phenomenon and whether the complexity and expertise required for AI play a role in fostering this conservative mindset or hindering its adoption. Moreover, expensive and resource-intensive AI initiatives and pilot projects do not assure the anticipated benefits, prompting the creation of the subsequent hypothesis:

H1.3: Complexity effects AI adoption negatively.

3.2 Organizational capability

Organizational capabilities encompass the diverse competencies essential for a company to effectively implement its business strategies and foster sustainable development (ZULU et al., 2022). These capabilities play a pivotal role in navigating the changes and challenges presented by the advancements of the Fourth Industrial Revolution (ZULU et al., 2022). They empower companies to adapt to the radical shifts in business models, regulations, and industries while addressing the intricacies and agility demanded by this revolution. Regarded as internal assets, organizational capabilities serve as the foundation for enterprise growth (WIKSTRÖM et al., 2022). Moreover, the concept underscores the significance of workplace conditions and practices that facilitate the utilization of skills among older employees, enhancing their quality of life and societal engagement. Ultimately, organizational capabilities are indispensable for ensuring the success and longevity of a company in an ever evolving and competitive environment.

Organizational capabilities encompass managerial capabilities, leadership resources, technical capabilities, and managerial support that bolster innovation adoption. These capabilities are non-transferable, typically organization-specific, and embedded within a company. The resource-based view (RBV) theory, according to Chen (2019), may be applied to determine organization-specific capabilities that support AI adoption. Companies gain a competitive advantage by incorporating economically valuable, difficult-to-imitate, and non-transferable resources, according to RBV theory (WERNERFELT, 1984; GARRISON et al., 2015). This indicates companies' distinctive and scarce resources may supply them with a competitive advantage in the short term. AI technologies can help businesses enhance efficiency (PERIFANIS & KITSIOS, 2023). They can gain an advantage over their competitors in this manner. As a result, organizational-specific capabilities distinguish companies from their competitors.

3.2.1 Managerial support

Scholars have recognized the significant role of top management support as an internal organizational factor influencing the adoption and implementation of IT innovations. Top management comprises individuals identified as potential company decision-makers (PREMKUMAR & RAMAMURTHY, 1995). Within the context of IT adoption, these individuals have indirect or direct associations in shaping the IT strategies within the organization. Researchers believe that managerial support is key in information system integration and technology adoption (THONG, 1999; MÜLLER & JUGDEV, 2012; CHONG et al., 2009; NAH et al., 2001). It is argued that strong top management support drives the development of organizational technology by encouraging the early adoption of IT innovations. In contrast, weak Leadership support hinders the organization's response to adoption (AL-DMOUR, LOVE & AL-DEBEI, 2016). Managerial support, on the other hand, refers to the assistance and guidance managers provide to their employees in the workplace. It encompasses providing resources, feedback, and encouragement to help employees effectively perform their jobs and achieve their objectives. Managerial support may manifest in various forms, such as offering training and development opportunities, providing flexible work arrangements, and addressing work-family conflicts (TRAVAGLIONE et al., 2017). The dedication of leaders is vital during significant corporate transformations as it guides the integration of services and the allocation of resources. (CO et al., 1998). Scholars argue that managerial support plays a crucial role in the integrating information systems and adopting technology. (CHONG et al., 2009; THONG, 1999; SANDERS & COURTNEY, 1985; NAH et al., 2001; MÜLLER & JUGDEV, 2012). For illustration, THONG (1999) suggests that the attributes of senior executives within firms impact their IT adoption. Similarly, as HAGE and DEWAR (1973) noted, top-level leaders who wield authority over resource allocation in organizations influence innovation adoption. Consistent and continual managerial support throughout the project implementation is crucial; otherwise, the project is at risk of failure (ELBANNA, 2013). The justification is that managers, especially those in top management, can appoint skilled personnel to oversee a project and allocate substantial financial and other resources to it. (WILLIS & SULLIVAN, 1984). A lack of managerial support, on the other hand, may harm the project (WIXOM & WATSON, 2001; PAJANY, 2021). The rapid innovations in emerging technologies are reshaping the managerial responsibilities of leaders. Utilizing remote intelligence (RI) and AI technologies enables organizations to outsource tasks more effectively. Consequently, leaders across all levels must possess the skills to lead, motivate, plan, and oversee virtual, diverse, and cross-cultural teams. They must also address global organizational disruptions, such as job displacement, inequality, and unemployment (FLOREK-PASZKOWSKA et al., 2021; SONG NG, 2021). Several scholars have linked the impact of technological disruptions to change management and the broader digitalization trend in industries, presenting new digital challenges and opportunities for established companies (SONG NG, 2021; GIONES et al., 2018). AI technologies hold the potential to significantly impact entire organizations, potentially bringing about substantial changes in business operations. The role of managers in IT adoption is crucial, particularly concerning AI applications, which necessitate managerial support and alignment with the company's strategic objectives. When managers possess a comprehensive understanding of AI technologies and their relevance to the organization's operations, they can effectively oversee their integration and usage within the company. Moreover, when leaders prioritize and comprehend AI applications as key initiatives, they demonstrate greater diligence and allocate resources accordingly (NAH et al., 2001). Additionally, managers must possess a concrete and clear comprehension of AI to maintain productive relationships with partners and vendors. Consequently, the following hypothesis is proposed:

H2.1: Managerial support influences AI adoption positively.

3.2.2 Technical capability

Technical capability encompasses an organization's proficiency, expertise, and resources to effectively perform tasks and remain competitive within specific markets and industries. This includes tangible assets like systems, machines, and equipment, as well as intangible elements such as skills, knowledge, and experience (SHETH et al., 2018). Investing in training programs and resources, including software, is advised to bolster technical capability, thereby enhancing organizational performance and competitiveness. According to ABOELMAGED (2014), "technical capability" refers to the tangible assets necessary for implementing innovations, such as data, networking infrastructure, and computer hardware. Concurrently, it represents a company's collective resources aimed at establishing a scalable and adaptable foundation for enterprise applications (WANG et al., 2016).

Additionally, Intangible assets, such as collaboration strategies, IT development processes, application methodologies, and technical expertise essential for effectively integrating cutting-edge technologies, constitute technical capability (GARRISON et al., 2015). Consequently, it is a crucial determinant influencing technology adoption (WU et al., 2007; GARRISON et al., 2015). It is claimed that aligning these technological attributes with the newly established technology significantly enhances its implementation. Furthermore, researchers in technology acceptance have highlighted the importance of considering the user's perspective on technological capability rather than focusing solely on organizational factors. They have emphasized factors such as user receptiveness to new information technology, individual personality traits, and the usability of the technology itself (YANG et al., 2015). Strong technical capability simplifies integration, allowing the IT team to deploy AI systems more quickly and efficiently. Successful adoption of AI applications hinges on a company's ability to achieve technological objectives and seamlessly integrate AI technologies into its existing infrastructure. The adeptness with which a company integrates emerging AI technologies across its IT framework directly correlates with its ability to reduce costs and efficiently allocate resources for profitable adoption. Whether utilizing freely available software or collaborating to develop an internal AI platform or tools, companies must fully comprehend the expertise, resources, and technologies required to realize AI's capacity. This generates the subsequent hypotheses.

H2.2: Technical capabilities positively affect AI adoption.

3.2.3 Managerial capability

Managerial capability pertains to managers' capacity to inspire, empower, and inspire workers to contribute effectively to the organization's efficiency and success (HOUSE et al., 2002). It encompasses fostering a robust workplace environment and culture, efficiently achieving goals, making decisions, and fostering innovation and creativity. In information technology, managerial capability involves coordinating projects, facilitating education, and providing training. GARRISON et al. (2015) also stated that managerial capability encompasses intangible assets that significantly impact IT adoption. TORNATZKY and FLEISCHER (1990) highlight that an organization is a source of frameworks, attitudes, culture, and procedures, that influence its IT adoption process. According to research (EMMELHAINZ, 1988), organisational resistance to change is the primary obstacle to the adoption of IT. As noted by WIXOM and WATSON (2001) state that effective managerial capabilities are demonstrated through clearly defined strategic plans and objectives, streamlined internal communication and collaboration, and comprehensive training and development initiatives within the organization. The emergence of AI introduces a novel approach to extracting insights from vast datasets.

Therefore, establishing an overarching strategic vision and plan for AI is essential as it is the cornerstone for AI adoption. The absence of a strategic plan and vision may impede IT innovations, as highlighted by (ANGELES et al., 2001). To accelerate AI adoption, companies require significant changes in business processes, such as formal education and training, an outstanding project management team, and good internal collaboration and communication.

Several organizational inhibitors, like a lack of a dedicated team, the absence of contact among company employees (GROVER et al., 1995), and insufficient training (Angeles et al., 2001), have been discovered to impede organizations' IT adoption. Businesses with powerful managerial capability can swiftly overcome such barriers and readily embrace innovative technologies. Within the ever-evolving landscape of organizational management, experienced leadership can enhance operational efficacy, craft apt marketing approaches, and foster resource utilization. This managerial insight empowers enterprises to anticipate emerging technologies and adeptly integrate them into their operations, aligning business practices with overarching objectives (GARRISON et al., 2015). Recently, AI applications have rapidly expanded, with numerous companies attempting to enter this domain. While it may be relatively straightforward for firms to initiate and invest in new AI technology, integrating it into existing organizational cultures and processes poses considerable challenges (RAJAMANICKAM et al., 2023). The successful adoption of AI hinges upon the managerial capabilities within the organization. Despite the objective nature of AI's innovation attributes in companies, they are perceived subjectively by employees, a perception that can be influenced by managerial ability. Suppose leaders can easily learn the possibility of using AI applications to enhance employees' practical value and professional skills, and subsequently adjust staffing, allocate resources judiciously, recruit suitable technical professionals, prioritize training, and create an environment conducive to AI adoption. In that case, the challenges associated with AI implementation can be mitigated. A proficient project management team, effective internal cooperation and communication, and proper training and education within a company can inspire employees' eagerness to learn, improve their readiness to embrace AI technologies and mitigate possible risks. This would significantly reduce negative sentiments and conflicts among workers arising from the challenges and complications associated with AI technologies and applications. Essentially, AI would align more seamlessly with existing cultures and processes. A high managerial capability enhances perceptions of the new technology's relative advantages and compatibility while diminishing perceptions of technological complexity or risks. Consequently, the business can adopt AI technologies and applications swiftly, gain competitive advantages, and enhance performance. Therefore, the following hypotheses were posited:

H3.1: Managerial capabilities affect the compatibility of AI positively.

H3.2: Managerial capabilities positively affect the relative advantage of AI.

H3.3: Managerial capabilities affect the complexity of AI negatively.

Managerial capability may impact managerial support. Typically, organizations have three tiers of managers: upper, middle, and frontline managers (FLOYD & LANE, 2000). Each management level concentrates on distinct facets of the company, spanning strategy, communication, and operations. A company's management cadre encompasses managers from these three tiers. Managerial capability conveys the aptitude of these leaders to assemble and organize resources to meet organizational objectives (ADNER & HELFAT, 2003). In contemporary enterprises, viewed as intricate and extensive systems, the management team typically performs most managerial tasks and decision-making responsibilities. A robust managerial capability signifies an efficient management ensemble that is important for any organization.

Moreover, according to KOR and MESKO (2013), managerial capability can shape leaders' predominant mindset. Consequently, over time, managers' predominant logic evolves and integrates company-wide policies, practices, and resources to establish an overarching logic at the organizational level, potentially reshaping decision-making processes and operational procedures (LAITILA, 2018; KOR & MESKO, 2013). An organization with a professional leadership team typically exhibits streamlined communication and collaboration channels, structured training initiatives, and sustained competitive advantage. Consequently, heightened managerial capability within the company, coupled with a highly efficient management team, garners greater recognition and endorsement from the organization's top leadership. No CEO favours an ineffectual leadership team. Hence, proposals and strategies devised by a strong and efficient management ensemble are more likely to secure managerial backing. Hence, the following hypothese was formulated:

H3.4: Managerial capabilities influence the managerial support positively.

Managerial capability also plays a role in shaping technical capability. Technical capability encompasses tangible assets such as networking infrastructure, software, and hardware, as well as intangible assets like problem-solving methods and technical expertise. According to KETTINGER et al. (2015), an organization's technical capability combines managerial procedures, software, hardware, shared services, and technical expertise. Yet, the physical components of IT capability alone do not significantly contribute to gaining a competitive advantage, as they are readily accessible to competing firms. Once a company adopts a new system or technology, competitors frequently emulate it, erasing the initial competitive edge. However, the intangible facets of IT capability are uncommon, non-reproducible, unique, and valuable assets for organizations. Intangible assets, such as collaboration strategies, IT development, application processes, and technical knowledge, can effectively incorporate the latest technologies (Garrison et al., 2015). These encompass the expertise, understanding, proficiencies, and mindsets essential for managers to organize IT resources and effectively integrate modern technologies. Therefore, these intangible assets of IT capability can be regarded as a specialized type of managerial proficiency. Managerial capability encompasses leadership competencies and coordination that facilitate the advancement of innovation in new technologies, as highlighted by BHARADWAJ (2000). Strong managerial capability has the potential to influence organizational culture positively, elevate employee competence, optimize both external and internal communication efficiency, expedite the implementation of technical solutions required for merging AI technologies, and achieve corporate objectives. A proficient management team equipped with strategic foresight can foster a dynamic atmosphere, allocate resources judiciously, identify and recruit skilled IT managers and technical experts, and establish an environment conducive to technological innovation, enhancing the organization's overall technical capabilities. Consequently, the following hypothesis was formulated:

H3.5: Managerial capabilities are positively associated with technical capabilities.

3.3 External environment

The external environment, encompassing industry dynamics, regulatory frameworks, competitors, and governmental interactions, serves as the operational backdrop for businesses (CHAU & TAM, 1997). The Institutional theory underscores the significant role of institutional culture in shaping organizational behaviour and structure (SCOTT, 2008). Further, GIBBS and KRAEMER (2004) also highlight the influence of the external environment on businesses. Consequently, organizational decisions are not solely driven by rational efficiency goals but also influenced by legitimacy, cultural, and social considerations. The external environment can present both encouragements and obstacles for companies adopting modern technologies. External pressures from the government, competitors, and customers often drive firms towards adopting and utilizing AI (GIBBS & KRAEMER, 2004). This research mainly focuses on government involvement, competitive pressure, market uncertainty, and vendor partnerships as external environmental factors.

3.3.1 Government involvement

Government involvement fosters IT technology (LEMKE, 2003; MOGEL, 2003). As highlighted by HUANG and PALVIA (2001), authority intervention can both promote the diffusion of IT and eliminate obstacles to introducing modern IT techniques. Governments can formulate supportive plans and policies to encourage the commercialization of emerging technologies and establish regulations conducive to technological development. STOICA et al.

(2005) emphasized the significance of government frameworks in shaping the adoption of new technologies, recognizing it as a multifaceted process. AI, a disruptive technology with far-reaching implications, raises numerous matters, including privacy, security, and ethical considerations.

Consequently, there is a pressing need for robust legislation and regulatory frameworks governing AI. The rapid advancement of AI technology exacerbates conflicts and challenges related to legal, employment, security, ethical, and governmental control issues. Therefore, comprehensive national-level planning and legislation regarding AI are imperative to foster the healthy growth of the AI industry. Recognizing that AI permeates nearly every aspect of human life and governments, society worldwide has allocated significant resources to invest in AI technology and has introduced national-level AI advance policies and plans (MARKRAM, 2012; DUTTON, 2018; NITRD, 2016; HALL & PESENTI, 2017). Government support provides a conducive atmosphere for the advancement of AI and is instrumental in fostering the dissemination and impact of AI technologies (AGRAWAL et al., 2018). Establishing and maintaining positive relations with governmental bodies is essential for AI providers to access the support and resources necessary for promoting new AI applications. Hence, the following hypothesis was formulated:

H4.1: Government involvement is positively associated with AI adoption.

3.3.2 Competitive pressure

Competitive pressure represents a significant force that shapes attitudes and decision-making processes within contemporary companies. It refers to the degree of competitive force sensed by an organization from its rivals (OLIVEIRA & MARTINS, 2011). Competitive pressure has consistently been identified as a significant predictor in research on adopting and spreading IT innovations (OLIVEIRA & MARTINS, 2011). Analysts and studies suggest that competitive pressure will persistently intensify as the global economy shifts toward a knowledge-driven and open-market framework. Consequently, companies are compelled to compete using all feasible avenues (AL-DMOUR et al., 2016). The progression and innovation in IT have become pivotal in this competitive landscape, with companies viewing it as a chance to enhance efficiency and quality, bolstering their competitive edge. PREMKUMAR and RAMAMURTHY (1995) underscored adopting the latest technologies as a strategic imperative amid extreme competition. Competitive pressure serves as a stimulant for technological advancement. Embracing modern technology frequently becomes a strategic imperative for staying competitive (NOVAKOVA, 2020; SCHWAB, 2017; SUMNER, 2000). The competitive advantages of firms are temporary rather than enduring.

Furthermore, PORTER and MILLAR (1985) suggest that innovation in IT can reshape business dynamics, redefine competition norms, introduce novel methods to outshine competitors and transform competitive conditions. MANSFIELD et al. (1977) discovered that intense market competition hastens the swift dissemination of IT technologies. Competitor pressure is a critical element in the adoption of IT (KUAN & CHAU, 2001; GIBBS & KRAEMER, 2004). Several studies have examined the effect of competitive pressure on adopting IT innovations. While a substantial amount of empirical evidence has supported the idea that competitive pressure is a significant determinant and a strong motivator for IT adoption and diffusion, researchers have conflicting views. For example, LOW et al. (2011) found in their study that competitive pressure, and pressure from trading partners, had a notable impact on using cloud computing.

Similarly, research on e-business adoption (OLIVEIRA & MARTINS, 2011; LIN & LIN, 2008) and business intelligence adoption (BHATIASEVI & NAGLIS, 2018) has yielded varying results viewing the impact of competitive pressure. On the contrary, some empirical findings contradicted this notion, suggesting that competitive pressure may not be a significant environmental factor. For example, OLIVEIRA et al. (2014) discovered no statistically significant evidence indicating that competitive pressure influences the adoption of cloud computing. When examining competitive pressure, two key factors must be taken into account. Firstly, industry-specific characteristics play a significant role. The level of competitive pressure differs depending on the industry and local market conditions.

Simply put, as the number of competitors within a particular market increase, so does the intensity of competition. In theory, if competitors are adopting innovations at a higher rate, non-adopters are likelier to adopt them (AL-DMOUR, 2014). The second aspect concerns the phase of IT innovation diffusion. It is suggested that competitive pressure escalates as the adoption phases progress. In simpler terms, during the early adoption stages, there might be less significant pressure compared to the later stages, where the IT innovation has been thoroughly tested and its value has been assessed. Embracing new technologies is frequently essential for businesses to stay competitive. When competitors adopt certain new technologies, companies often feel pressured to integrate them swiftly to sustain their competitiveness (OLIVEIRA and MARTINS, 2008). Companies that effectively utilize new AI technologies to improve their offerings gain competitive edges over rivals. Hence, the pressure from competitors motivates firms to adopt AI applications and technologies. This forms the basis for the following hypothesis:

H4.2: Competitive pressure positively influences AI adoption.

3.3.3 Market uncertainty

Market uncertainty encompasses the unpredictability and lack of clarity inherent in commercial markets, posing challenges for businesses in making well-informed decisions and strategizing for the future. This phenomenon permeates various sectors, such as healthcare, international trade, and the economy as a whole. Market Factors, including product demand, competitive intensity, and customer loyalty, are beyond companies' direct influence yet significantly impact their operational outcomes (HAO et al., 2018). In any commercial market, uncertainties abound, presenting a mix of risks and opportunities. Those adept at identifying opportunities amidst market volatility stand to gain competitive advantages. Market uncertainty significantly influences the adoption of artificial intelligence (GANS, 2023a). The benefits firms derive from AI adoption are shaped by the trade-offs they encounter in setting prices and quantities ahead of demand, which are affected by market uncertainty (GANS, 2023b). Diverse industrial settings, characterized by varying flexibility in pricing and quantity adjustments post-adoption, also impact the returns of AI adoption (HONG & CHO, 2023).

Moreover, the time horizon of AI prediction plays a role in determining its impact on firms. In competitive markets, adopting AI has been shown to increase the short-run elasticity of supply. It may or may not increase average equilibrium costs, depending on specific market conditions (SCHMIEGELOW & MELO, 2023). Overall, market uncertainty is a critical factor influencing the adoption and impact of AI across different industries. Numerous nations and organizations have announced plans for AI advancement or introduced regulations to capitalize on the opportunities presented by AI. While many AI applications and technologies are still developing and face a shortage of qualified professionals and technical experts, AI has demonstrated robust potential and offers companies enhanced competitive prospects. For instance, voice assistants and chatbots for customer service can enhance operational efficiency and reduce labour costs.

Additionally, AI technologies are indispensable for complicated tasks like fingerprint recognition and face detection. By leveraging AI, businesses can attract new clientele and bolster customer loyalty. Despite the vast market potential of AI applications, the current landscape of AI implementation remains largely uncharted. This lays the groundwork for the following hypothesis:

H4.3: Market uncertainty is negatively associated with AI adoption.

3.3.4 Vendor partnership

Vendor partnership means the cooperative alliance between an organization and its suppliers, to achieve shared benefits and objectives. It entails fostering a close and strategic relationship with suppliers rather than adopting an adversarial approach. The efficacy of vendor partnerships may vary depending on diverse circumstances and environments. Additionally, such partnerships may encompass collaborative technology development by both the manufacturer and the vendor, which may be advantageous under specific circumstances. Enhancing vendor relationships through communication and collaboration can ultimately reduce the organisation's cost (FINDIKOGLU et al., 2021). Many companies lack the internal technical and transformative expertise necessary to effectively manage technologies such as AI.

Consequently, AI implementation in companies often involves collaboration with external partners and IT vendors, as many companies are inexperienced with AI technologies. As per ASSAEL (1984), the participation of vendors can notably impact the pace of adoption and spread of new products. Empirical evidence supports vendor partnerships as a critical factor in adopting innovation (YANG & KANKANHALLI, 2013; SULAIMAN & WICKRAMASINGHE, 2014; AHMADI, et al., 2015). Recently, many businesses have primarily trusted vendors who adhere to industry standards for their IT and network technologies. Yet, these vendors may not be the optimal source for AI applications. Suppliers have a distinct and important role in the field of AI. They typically require extensive data, often including sensitive customer information, to develop their AI tools. As a result, vendors may not offer ready-to-use AI applications; instead, they need to collaborate closely with firms (their clients) to conduct AI training during and after implementation. Companies must streamline the management process and data collection to engage with AI-leading vendors effectively, facilitating utilisation AI technologies. Hence, the following hypothesis was formulated:

H4.4: Vendor partnership is positively associated with AI adoption.

4. MATERIALS AND METHODS

This chapter comprehensively describes the study methodology utilized to address the research inquiries. Additionally, it introduces the research design, study approach, sampling strategy, data collection methods, research population, data sources, data analysis procedures and techniques, and research instruments. Furthermore, it explains the parameters that ensure research quality as well as the ethical considerations considered in the reserch design.

4.1 Research Design

A research design is established to determine various aspects, including methods for gathering additional data, analysing and interpreting it, and ultimately providing a solution to the research problem. As defined by SEKARAN and BOUGIE (2016), research design is a structured blueprint or plan formulated to collect, evaluate, and analyse data to address research inquiries. This implicates making decisions regarding various design elements, each of which significantly influences the effectiveness and quality of the research. These elements encompass research strategy, a unit of analysis, researcher involvement, study environment, and timeframe. Furthermore, it entails defining data collection methods, measurement tools, and sample design (SEKARAN & BOUGIE, 2016). The research design serves as a guiding framework for the analysis processes and data collection, assuring that the processes employed are optimal for elucidating and achieving the research purposes.

4.2 Research Approaches

Business research is a structured, methodical, data-driven, analytical, impartial examination of a particular problem (SEKARAN & BOUGIE, 2016). Research methodology is the systematic approach and philosophy employed in scientific research to solve a research problem, collect data using various methods, analyze the collected data, and draw conclusions. (SEKARAN & BOUGIE, 2016; VIKTORIIA et al., 2022). There are three main types of research methodology: qualitative, quantitative, and mixed methods, which incorporate both quantitative and qualitative approaches. Qualitative research studies social issues by exploring the subjective meanings attributed to individuals. Data are collected in natural settings through open-ended questionnaire responses, interviews, and observations. Conversely, the quantitative approach seeks to generate understanding and interpretation within a structured framework (CRESWELL, 2009). Numeric data are gathered, and statistical analysis techniques are employed to explore the relationships among the variables under study objectively. Data collection involves structured questions to minimize subjective judgment or bias (CRESWELL, 2009). Mixed methods research integrates quantitative and qualitative approaches to address questions that a single method cannot adequately answer. It targets to gather, analyze, and blend both types of data to enhance the study findings compared to relying solely on one approach (SEKARAN & BOUGIE, 2016). The research approaches encompass two primary types: First, the quantitative research form involves quantifying data collection and analysis, typically employing deductive reasoning with a sequential procedural flow (BRYMAN & BELL, 2015). Quantitative data are numerical and commonly acquired through structured questioning (SEKARAN & BOUGIE, 2016). In addition, CRESWELL (2014) indicated that quantitative research supports researchers seeking to grasp the relationships between variables. Quantitative research helps to examine theories, measure variables, test the relationship between variables, and investigate phenomena in large groups (LEEDY & ORMROD, 2005).

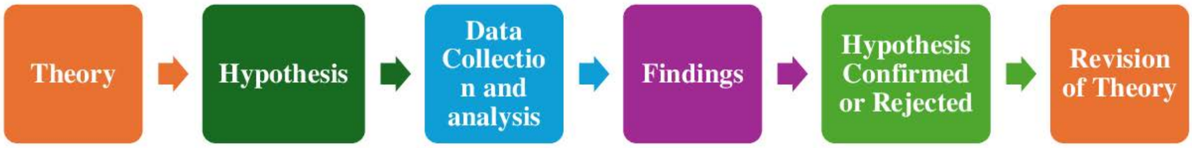

Figure 4. The research flow process for the qualitative data

Source: edited by Author from (SEKARAN & BOUGIE, 2016)

On the other hand, the qualitative approach prioritizes verbal expressions over quantification and employs an inductive method of reasoning, which contrasts with deductive reasoning (BRYMAN and BELL, 2015). Figure 4. shows the flow process for qualitative data. DENZIN and LINCOLN (2005) characterize qualitative research as an activity situated within the context that places the observer in the world. It involves a collection of interpretive, concrete methods that make the world discernible. Meanwhile, MILES and HUBERMAN (1994) describe qualitative research as providing deeply rooted, thorough descriptions and explanations of processes occurring within a distinct local context. DENZIN and LINCOLN (2005) contend that qualitative inquiries must align with the research framework, whether confirmatory or exploratory, and connections must be established between the data and the research framework to enhance the effectiveness of qualitative research. Approaches like meetings, participant observation, and communication are regarded as qualitative approaches that yield rich data and information. In Table 4, we outline the distinctions between quantitative and qualitative data.

Table 4. the differences between the quantitative and qualitative data

Quantitative data	Qualitative data
Derived from numerical interpretations	Derived from interpretations conveyed in language
Gathering yields data that is numerical and standardized	Gathering produces data that is not standardized and needs to be categorized.
Analysis performed utilizing both statistical methods and diagrams	Analysis carried out through conceptualization

Source: edited by Author from SEKARAN and BOUGIE (2016)

As mentioned, this study will utilize mixed methods approaches incorporating both quantitative and qualitative methods without specifying the specific methods emphasized by the research. This approach allows researchers to blend inductive and deductive reasoning and employ various methods to accomplish their research objectives. Figure 5 shows a simplified overview of the research approach.

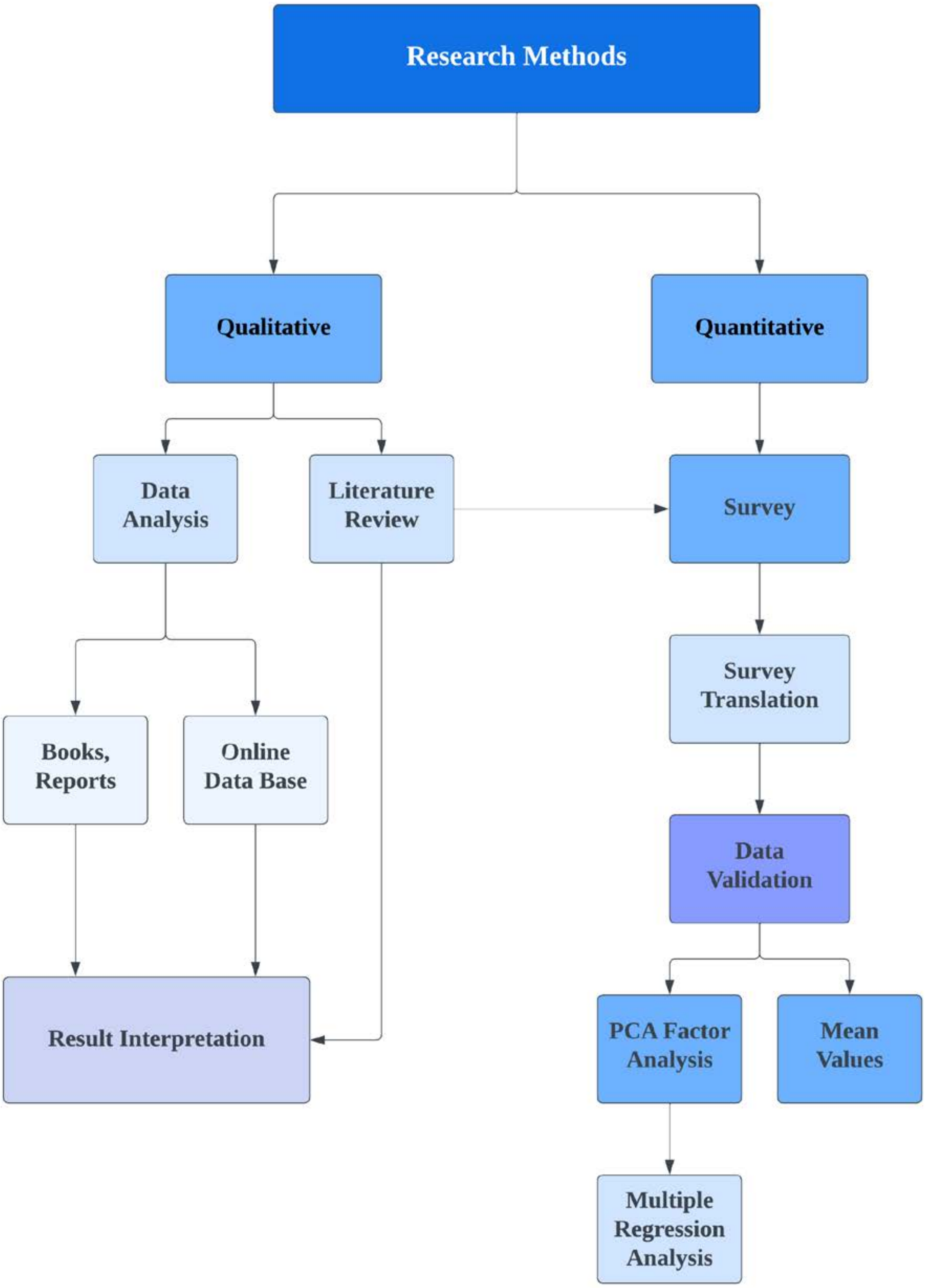

Figure 5. An overview of the research Methods

Source: Author's Creation (2024)

4.3 Research Strategy

The research strategy constitutes a predetermined plan devised to achieve study objectives and provide a scientific resolution to research questions. Therefore, selecting a research strategy is closely intertwined with the research questions, research objectives, the researcher's perceptions regarding the appropriateness of the strategy, and practical research considerations (SEKARAN & BOUGIE, 2016). In this research, the objective is to examine the propsed hypotheses empirically. Consequently, a conceptual model has been developed to illustrate the proposed research hypotheses concerning the relationships between the study variables. Hypotheses represent logical speculations regarding the relationships between two or more variables and enhance understanding of the phenomenon under investigation through testable statements (SEKARAN & BOUGIE, 2016). By testing the hypothesized correlations, conclusive answers are obtained regarding the postulated relationships within the research variables. Therefore, this research uses a survey approach to outline the importance of specific predictors and their influence on AI adoption in companies. As well as establish a guide to the most effective factors of AI adoption in firms and test the inner constructs of hypothesized relationships.

4.4 Data Collection Methods

This study is based on two sources of data: secondary and primary. First, the primary data refers to data gathered expressly for the particular study project (SAUNDERS & LEWIS, 2012). (SAUNDERS & LEWIS, 2012). It can be obtained through various methods, such as administering questionnaires, conducting interviews, and observation. The survey consists of predetermined written questions that participants respond to by selecting from specified alternatives (SEKARAN & BOUGIE, 2016). Questionnaires are commonly employed to gather an enormous volume of quantitative data and can be distributed in person, electronically, or via mail (SEKARAN & BOUGIE, 2016). Nevertheless, each approach has its own set of pros and cons (refer to Figure 6).

The primary data collection method for this study involves employing an online questionnaire. Utilizing electronic or online questionnaires offers a quick and convenient means of distribution. An online questionnaire was Initially utilized to gather data supporting the research objectives and offering more profound insights. Online surveys offer researchers the advantage of easy access to the target demographic and the ability to reach a wide geographical area. Moreover, they save time, expenses, and effort.

In addition to the advantages outlined above, various practical and methodological factors have contributed to the preference for electronic questionnaires, including the COVID-19 pandemic necessitating lockdowns and emergency measures, as well as simplified distribution, response handling, and coding processes. Due to the low response rate, further action was required; therefore, personally administered questionnaires were conducted to obtain the necessary responses.

Data Collection	Advantages	Disadvantages
Personally Administered Questionnaires	Can establish rapport and motivate respondents and doubts can be clarified. Anonymity of respondent is high. Less expensive when administered to groups of respondents. Almost 100% response rate ensured.	Explanations may introduce a bias. Takes time and effort.
Mail Questionnaires	Wide geographic regions can be reached, and Anonymity is high. Can be administered electronically. Token gifts can be enclosed to seek compliance. Respondent can take more time to respond at convenience.	Response rate is almost always low. A 30% rate is quite acceptable. Cannot clarify questions. Follow-up procedures for nonresponses are necessary.
Electronic Questionnaires	Easy to administer and can reach globally. Very inexpensive and Fast delivery. Respondents can answer at their convenience, like the mail questionnaire. Automatic processing of answers.	Sampling issues and High non-response. Computer literacy is a must. People find invitations via email rude and offensive; emails are deleted, or people complain. Not always possible to generalize findings.

Figure 6. Advantages and Disadvantages of Questionnaire Types

Source (Sekaran & Bougie, 2016)

Secondary data refers to information gathered for purposes other than the current research. It is an adaptable resource offering numerous advantages, including accessibility and ease of analysis, time efficiency, cost-effectiveness, and non-intrusive nature. Additionally, secondary data provides a wealth of related information in various formats and methodologies, enhancing understanding and offering comparative context for the study project (SAUNDERS & LEWIS, 2012). These secondary data predominantly consist of written materials such as books, reports, journal articles, and annual reports about the research topic. The secondary data were obtained in digital and physical forms by search terms formulated by the researcher and by reviewing relevant literature. Additionally, the secondary data have made the following significant contributions: defining the research variables by comparatively assessing their significance in the literature, enhancing the comprehensive understanding of research on IT innovation adoption, observing factual information and analytical patterns, Guiding the selection of research methodology and informing the choice of data collection methods, and Identifying gaps and deficiencies in existing research.

4.5 Research Context

The telecommunications industry has been chosen as the research context for the current study because it has undergone a significant shift post-2000. This transition has seen a move from Internet services and traditional telephones to expanded, data-centric networks, marked by a shift from voice calls to video and data services. This evolution has presented numerous challenges, particularly in digital transformation. On one hand, there is a growing demand for faster data connectivity, high-resolution content, and multimedia applications. On the other hand, competition from web-scale companies has intensified. To address these challenges, telecom operators focus on expanding subscriber bases by enhancing services and embracing modern technologies like the IoT and 5G networks. However, the implementing such technologies brings complexities to network architecture and operations. The emergence of 5G networks, with their distributed nodes and advanced technologies, necessitates using AI for efficient management and maintenance. Telecom networks offer vast potential for AI integration, presenting opportunities for enhancing network elements and business systems. Some operators are already experimenting with AI-driven solutions for both customer-facing services and internal operations, with strategic plans in place for further integration of AI technologies, such as AT&T's initiative to virtualize a significant portion of its network by 2020 (CASTRO et al., 2018; XU & DUAN, 2018; ZHANG & LORENZ, 2018).

The telecom industry is poised to become a key driver of AI development and a prime domain for AI applications. Currently, 294 telecommunication companies are operating in Hungary, based on the EMIS.com database.

4.6 Research Instruments

The framework of this study encompasses eleven latent variables. To explore their relationships with AI adoption in firms, an online survey was created based on prior studies and literature related to DOI theory, TOE theory, and IT adoption. The Likert 7-point scale ranged from 1 for strongly disagree to 7 for strongly agree. The survey comprises 47 questions intended for leaders and engineers within firms (refer to appendix 1A). It has also been translated into Hungarian. Additional information about the questionnaire is available in Appendix 1.

The process of developing the questionnaire involves multiple steps to provide a structured framework to ensure its efficacy and the suitability of the collected data for testing our hypotheses. The questionnaire is crafted by incorporating elements from past literature on diffusion, innovation, implementation, and adoption of IT. The summary of these instruments and the demographic data is shown in Table 5. This research utilized an English language instrument to address language barriers. TOMA et al. (2017) outlined various methods for translating research instruments, including backwards, forward, and cognitive translation. In backward translation, the instrument in the target language is translated back into the original language and assessed for any discrepancies and alignment of meaning. One or more language experts translate the original instrument into the target language using the forward translation method.

On the other hand, the cognitive approach involves gauging the clarity and comprehension of the translated instrument by the intended respondents. This research employed a combined translation approach, encompassing several steps: initially, initially, a language expert translated the original instrument from English to Hungarian. Subsequently, another expert translated the Hungarian version back into English. The quality of the translation was then reviewed and evaluated by a third-language expert. Finally, three native Hungarian speakers assessed the clarity and identified any discrepancies in the final version.

Further the revised version was adopted for distribution to the targeted group. This study's selection of measurement scales was tailored to suit the nature of each question. Table 5 provides an overview of the instrument content, measures, and their sources. A nominal scale pertaining to sample characteristics was employed in the initial section of the questionnaire. In this measurement type, the numbers allocated to items have no quantitative significance other than indicating their presence or absence and cannot be subjected to arithmetic operations (HAIR et al., 2014).

This section comprised nine questions to gather data on respondents' company name, age, level of education, country, number of employees, current position, AI adoption level, AI applications, and annual sales. Subsequent sections of the questionnaire utilized a 7-point rating scale (Likert scale), where each item was independently scaled.

The Likert scale facilitates the categorization of responses based on the degree of disagreement or agreement and enables differentiation between response variations. These scales are easily analyzed and administered, particularly in online email questionnaires (HAIR et al., 2014).

The second section included 11 questions assessing innovation characteristics and factors, while the third section comprised 23 questions evaluating TOE construct factors. Last, four questions were employed toward AI adoption in firms.

Table 5.Questionnaire Instrument and demographic data

Construct	Variables	Number of Items	Scale of Measurement	Sources
Background Information	Company name	1	Short answer	Author Constructed
	Age	1	Multiple options	(CHEN, 2019)
	Level of education	1	Multiple options	(CHEN, 2019)
	Country	1	Short answer	Author Constructed
	Number of employees	1	Multiple options	(GARRISON et al., 2015)
	Current position	1	Multiple options	Author Constructed
	AI adoption Level	1	Multiple options	(CHEN, 2019)
	AI applications	1	Multiple options	(CHEN, 2019)
	Annual sales	1	Multiple options	(CHEN, 2019)
Total		9		
Innovation Attribuation of AI	Compatibility (C)	4	Likert Scale (1- 7)	(OLIVEIRA et al., 2014)
	Relative Advantage (RA)	4		(MARTINS et al., 2016; TEO et al., 2007; CHONG et al. (2009)
	Relative risk/Complexity (RC)	3		(MARTINS et al., 2016; WANG et al., 2016; CHONG et al.,2009)
Total		11		
Technological Organizational Environmental (TOE)	Government involvement (GI)	3	Likert Scale (1-7)	(CHANG et al., 2006, OLIVEIRA et al., 2014; YANG et al., 2013)
	Market factor /uncertainty (MF)	3		(CHAU & TAM, 1997)
	Vendor partnership (VP)	3		(HAN, et al., 2008; ZHU et al., 2003)
	Competitive Pressure (CP)	4		(OLIVEIRA et al., 2014)
	Managerial capability (MC)	3		(RAVICHANDRAN & LERTWONGSATIEN, 2005; GARRISON et al., 2015)
	Managerial support (MS)	4		(GARRISON et al., 2015; HAN et al., 2008)
	Technical capability (TC)	3		(GARRISON et al., 2015; HAN et al., 2008)
Total		23		
Artificial Intelligence adoption	AI adoption (AI)	4	Likert Scale (1-7)	(CHAU & TAM, 1997; REICH & BENBASAT, 1990).
Overall Total		47		

Source author's creation

4.7 Sampling Strategy

The population and sampling process play a fundamental role in the effectiveness of the study. The population refers to the entire group of people, things, or events of interest that the researcher desires to study (SEKARAN & BOUGIE, 2016). In line with the study's questions and objectives, this study explores the emerging factors related to using AI applications in firms. Specifically, examines the relationship between these applications, organizational innovation characteristics, environmental factors, and firms' attitudes toward AI adoption. Thus, attaining the study purposes relies heavily on the validity and representativeness of the collected data. This research targets top management and engineers from telecommunications firms located in Hungary. Managers and engineers are selected because they play a significant role in technology adoption, decision-making, and collaboration with internal and external AI partners.

Consequently, they possess expertise regarding the primary factors investigated in the dissertation. Moreover, their insights are deemed crucial and dependable. The firm's selection criteria will consider the the company's AI adoption level, the availability of their contact details, the firm size, and the AI application type. This study investigates customer chatbots and AI-based speech and voice service. Therefore, the selected company needs to fulfil the desired criteria.

The sampling frame refers to the comprehensive roster comprising all individuals within the population (SAUNDERS & LEWIS, 2012). A sample constitutes a portion of the population, consisting of selected members, indicating that only some aspects are included. The rationale for employing a sample instead of gathering data from the entire population is evident. In research endeavours encompassing hundreds or thousands of elements, collecting data from, testing, or analysing every element would be virtually unfeasible. Even if feasible, the endeavour would be impractical regarding time, cost, and other resources.

Additionally, studying a sample instead of the entire population is often expected to yield more reliable outcomes (SEKARAN & BOUGIE, 2016). Telecommunications businesses were selected because they are considered leaders in the AI field. Currently, 294 telecommunication companies are operating in Hungary, according to the EMIS.com database. The validated sample number for the chosen companies is 269. HAIR et al. (1998) propose that in quantitative research, the sample size should ideally be five times greater than the total number of measurement scale indicators. Considering this study's initial model with 38 observed indicators across 11 latent constructs, the recommended minimum sample size would be 38 * 5 = 190.

The data collection process commenced with gathering information via an online survey. Participants received an inbox message (refer to Appendix 1) containing details about the research introduction and objectives, a confidentiality declaration, and a link to the online questionnaire available in both English and Hungarian. The online survey commenced in May 2023. Due to low response rates during the COVID-19 period, further action was necessary, leading to the distribution of a printed version of the survey to companies in Budapest and Debrecen. Initially, 195 responses were gathered. Subsequently, the collected data underwent screening to identify and address missing values, suspicious responses, patterns, and outliers, following the guidelines outlined by HAIR et al. (2014). After this screening process, the number of valid responses decreased to 191, exceeding the minimum sample size of 190. Hence, the 191 responses met the criteria for conducting the research model.

4.8 Ethical considerations

Ethics in business research encompasses a set of principles or societal expectations governing behaviour during research endeavours. This ethical framework extends to the organization and its members funding the research, the researchers themselves, and the individuals supplying data. Upholding ethical standards commences with the researcher, who should approach the study with integrity, remain attentive to findings, and prioritize organizational interests over personal gain by setting aside ego. Ethical conduct is likewise essential for researchers, participants, analysts, and the research team through every phase of the study, involving data collection, analysis, reporting, and dissemination. This emphasis on ethical behaviour underscores the integrity and credibility of the research outcomes (adapted from SEKARAN & BOUGIE, 2016). This study takes several ethical considerations into account. Before conducting the survey, the survey instructions notify participants of the purpose, nature, estimated time required to complete the study, and the research name.

Additionally, all respondents were assured of confidentiality and anonymity, and participation in the survey was entirely voluntary. All information and data were handled with confidentiality and anonymity ensured. Please refer to the confidential statement in Appendix 1B for further details.

4.9 Data Analysis Procedures

In the realm of management study, scholars often encounter numerous challenges that may restrict the scope of their conclusions. Consequently, researchers must opt for suitable and stringent research methodologies. This entails assessing the influence of their choices regarding data analysis techniques, research instruments, and other factors that may prompt several inquiries about the conclusions drawn (SCANDURA & WILLIAMS, 2000). Nevertheless, for the research findings to be deemed valid, they must meet a certain threshold of reliability and validity, encompassing external, internal, construct, and statistical conclusion validity (TAN, 2019; SCANDURA & WILLIAMS, 2000). Reliability pertains to the consistency of measures utilized, while construct validity evaluates the degree to which these measures accurately represent the theoretical constructs. Internal validity assesses the presence of causality, confirming cause-and-effect relationships among the variables under investigation, whereas external validity gauges the extent to which the findings can be generalized beyond the study sample (TROCHIM, 2006; SCANDURA and WILLIAMS, 2000).

Lastly, statistical conclusion validity concerns the capacity to draw findings based on statistical evidence of covariation and prediction, focusing on sources of error contributing to variability and selecting an appropriate statistical test to address such errors (SCANDURA and WILLIAMS, 2000).

This part offers a description of the analysis process carried out. Initially, the data were transferred from the online Google survey to Excel format, and from the printed papers. Subsequently, data coding and editing processes were implemented, entailing the assignment of numerical codes to participants' response variables and scrutiny for inconsistent or illogical responses. Please refer to Table 6 for a summary of variable coding. For the Likert scale, spanning from "strongly disagree" to "strongly agree", a 1-7 coding system was applied.where 1= Strongly Disagree, 4=Neutral, and 7=Strongly Agree. To accomplish the study goals, various statistical analyses are used. Initially, a demographic analysis description is performed to outline the fundamental attributes of the data in the study and offer an overview of the respondents' demographic traits.

The subsequent stage involved evaluating the validity and reliability of the instrument. This entailed analyzing the suitability and sufficiency of the sample for factor analysis by assessing various aspects such as items, communalities, Kaiser Meyer Olkin (KMO), and total variance explained. Factor analysis is a statistical technique to discover latent factors that elucidate the relationships among observed variables (KOSFELD & LAURIDSEN, 2008). Once adequacy was confirmed, factor analysis was conducted utilizing Principal Component Analysis (PCA), which involved component and common factor analysis to evaluate the instrument's validity.

Additionally, the reliability of the measurement scale was assessed by calculating Cronbach's alpha value. Subsequently, the appropriateness of the research data for regression analysis was examined through normality assessments, and multicollinearity. Finally, multiple regression analysis was employed to test the predicted relationships hypothesized in the research. SPSS software will be used to analyze the data for regression analysis.

Table 6.Variable coding summary

Variables	Variable code
Compatibility	C1 to C4
Relative Advantage	RA1 to RA4
Relative risk/Complexity	RC1 to RC3
Government involvement	GI1 to GI3
Market factor /uncertainty	MF1 to MF3
Vendor partnership	VP1 to VP3
Competitive Pressure	CP1 to CP4
Managerial capability	MC1 to MC3
Managerial support	MS1 to MS4
Technical capability	TC1 to TC3
AI adoption	AI1 to AI4

Source author's creation

5. RESULT AND RESEARCH FINDINGS

This chapter discusses the outcomes derived from the quantitative analysis of research data. It includes testing research hypotheses and the subsequent presentation of findings and conclusions regarding the relationships among the research variables outlined in the research Model. The analysis involves managing, converting, and evaluating data using SPSS 25 software to derive meaningful insights corresponding to research inquiries.

5.1 Descriptive Statistics

In this section, the objective is to provide a concise overview of the data presented and outline the characteristics of a sample, which includes various statistical measures like measures of variability (e.g., standard deviation, variance) and measures of central tendency (e.g., median, mean), along with graphical representations like histograms and box plots. Descriptive statistics play a vital role in assessing the representativeness of a sample, aiding in decision-making processes, and guiding future research endeavours. They serve as a fundamental tool for summarizing data through frequency distributions, measures of central tendency, and variability, laying the groundwork for further statistical analyses. The subsequent section will delve into a Description of Demographic Analysis, where frequencies and percentages will be discussed.

5.1.1. Demographic Analysis Description

The research sample comprised 191 valid responses. Demographic data pertinent to the research objectives were collected through the questionnaire, including information on education, age, annual sales, number of employees, current position, AI applications, and current level of AI utilization. Table 7 displays the distribution of respondents across these specified categories.

The current level of AI adoption within the sample reveals that the highest category of respondents fell within the 2 to 5-year range, comprising 87 responses, or 45.5% of the total. Conversely, the "Not Considering" category was the lowest category of respondents, totaling 3 respondents, or 1.6%. For AI applications, the Intelligent Network Management category had the highest percentage of respondents within the AI Applications category, with the number of respondents reaching 78, representing 40.8%. This was followed by the Chatbot category, with 40 respondents accounting for 20.9%. The Build Artificial Intelligence Platform category accounted for 18.8%. Other categories included Customer Relationship Management (CRM) and Virtual Network Functions (VNFs).

Table 7. Demographic characteristics of the study sample members

Properties	Category	Repetition	percentage
AI currently	Not considering	3	1.6%
	More than five years	59	30.9%
	Between two and five years	87	45.5%
	between one and two years	11	5.8%
	Less than one year	8	4.2%
	Have already adopted service, infrastructure or platforms of AI	23	12.0%
	Total	**191**	**100%**
AI Applications	Chatbot	40	20.9%
	Voice Assistant	28	14.7%
	Intelligent Network Management	78	40.8%
	Build an Artificial Intelligence Platform	36	18.8%
	Others	9	4.7%
	Total	**191**	**100%**
Current Position	General manager	21	11.0%
	Senior manager	42	22.0%
	Middle manager	33	17.3%
	line manager	18	9.4%
	Team leader	35	18.3%
	Engineer	17	8.9%
	Others	25	13.1%
	Total	**191**	**100%**
Employees Number	Less than 500	135	70.7%
	500-999	16	8.4%
	1000-1999	10	5.2%
	2000-2499	17	8.9%
	Over 2500	13	6.8%
	Total	**191**	**100%**
AnnualS	Less than 100 million	117	61.3%
	100-499 million	46	24.1%
	500-1 billion	16	8.4%
	over 1 billion	12	6.3%
	Total	**191**	**100%**
AGE	Less than 30	94	49.2%
	31-40	75	39.3%
	41-50	13	6.8%
	51-60	8	4.2%
	More then 60	1	0.5%
	Total	**191**	**100%**
EDU	High school	40	20.9%
	Bachelor degree	109	57.1%
	Master's degree	35	18.3%
	Doctoral	7	3.7%
	Total	**191**	**100%**

Source: Author's creation

For the Current Position, the results indicated that the highest percentage of respondents fell into the Senior Manager category, with 42 responses, representing 22.0%. The Team Leader category followed, with 35 responses, accounting for 18.3%. The lowest percentage was for the Engineer category, with 17 responses, or 8.9%. Other categories included Site Operations

Manager, IT Engineer, and CEO, comprising 13.1%. For the Number of Employees, the category Less than 500 had the highest percentage of respondents, with 135 responses, accounting for 70.7%. Following this was the 2000-2499 category, with 17 responses, representing 8.9%. The 500-999 category had a percentage of 8.4%, and the lowest was the 1000-1999 category, with 5.2%. In the annual sales, the category with less than 100 million respondents had the highest percentage of respondents, with 117 responses representing 61.3%. The 100-499 million category followed, with 46 responses, accounting for 24.1%. The 500-1 billion category had 8.4%. For the Over 1 billion category, there were 12 responses, comprising 6.3%. The highest percentage of respondents in the AGE category was in the less than 30 category, reaching 49.2%. Following this was the 31-40 category, with a percentage of 39.8%. The lowest response rate was from the category of more than 60, at 0.5%. And finally, in the Education Level category, the results showed that the highest percentage of respondents had a bachelor's degree, accounting for 57.1%. Following this was the high school category, which comprised 20.9%, followed by the Master's degree category. The lowest percentage was for the Ph.D. degree.

5.1.2. Distribution Normality

Normality denotes the extent to which the distribution of sample data adheres to a normal distribution pattern. According to statistical standards, if the deviation from a normal distribution is significant, all ensuing statistical tests are invalid, as normality is a prerequisite for utilizing t and F statistics. As per (HAIR et al., 2014), researchers must examine statistical examinations and graphical plots to measure the degree of departure from normality. Additionally, evaluating the significance level of deviations from the normal distribution is crucial to ascertain the appropriateness of data for specific analytical techniques. To assess the normality of the study data, the initial step involves examining a graphical P-P plot and conducting kurtosis and skewness analyses. The P-P plot, detailed in Appendix 2, demonstrates the absence of substantial deviation of data points from the probability line. The alignment of residuals from study variables with this line suggests a normal data distribution. Alongside the visual inspection, a statistical assessment of normality is conducted by evaluating kurtosis and skewness values. Skewness characterizes the distribution's balance, indicating whether it is symmetrically centered with a similar shape on both sides, positively skewed to the left, or negatively skewed to the right. Conversely, kurtosis measures the "peakedness" or "flatness" of the distribution's height compared to a normal distribution (HAIR et al., 2014). Table 8 displays the Kurtosis and Skewness values for the study variables.

Table 8. Statistical Test of Normality

Items	Minimum	Maximum	Mean	Std. Deviation	Skewness	Kurtosis
GI1	2	7	5.52	1.156	-.593	-.016
GI2	2	7	5.48	1.099	-.576	.152
GI3	2	7	5.49	1.191	-.544	-.316
MF1	2	7	5.82	1.017	-.747	.945
MF2	2	7	5.93	.932	-.918	1.878
MF3	3	7	5.98	.891	-.690	.472
CP1	3	7	5.95	.928	-.775	.599
CP2	3	7	5.52	1.204	-.421	-.771
CP3	3	7	5.98	.906	-.560	-.103
CP4	3	7	6.01	.846	-.652	.463
VP1	2	7	5.44	1.177	-.422	-.296
VP2	2	7	5.59	1.072	-.448	.170
VP3	1	7	5.68	1.128	-1.088	1.427
MC1	2	7	5.39	1.195	-.313	-.402
MC2	4	7	5.77	.887	-.320	-.591
MC3	3	7	6.11	.836	-.866	.952
MS1	2	7	5.47	1.094	-.534	.093
MS2	2	7	5.26	1.130	-.320	-.420
MS3	1	7	5.23	1.183	-.225	-.142
MS4	3	7	5.54	.916	-.340	.185
TC1	1	7	5.29	1.195	-.686	1.102
TC2	2	7	4.92	1.432	-.339	-.656
TC3	2	7	5.78	1.033	-.908	1.069
C1	2	7	5.30	1.047	-.441	.405
C2	2	7	5.51	1.051	-.447	.215
C3	2	7	5.52	1.095	-.655	.558
C4	2	7	5.38	1.121	-.379	-.017
RA1	3	7	5.88	.941	-.561	-.013
RA2	3	7	5.57	1.008	-.228	-.649
RA3	2	7	5.62	1.023	-.620	.683
RA4	3	7	5.81	.987	-.608	.092
RC1	1	6	3.81	1.304	-.134	-.610
RC2	2	7	4.89	1.033	-.415	-.144
RC3	2	7	4.95	1.176	-.556	.022
AI1	3	7	5.13	.897	-.162	-.161
AI2	2	7	4.98	1.034	-.257	-.271
AI3	2	7	5.07	.987	-.580	.705
AI4	3	7	5.42	.854	-.170	-.201

Source: Author's calculations using SPSS

A skewness value of zero indicates a perfectly normal distribution for a variable. Similarly, kurtosis values equal to zero indicate a perfectly normal distribution (KIM, 2013). Therefore, the closer the absolute skewness and kurtosis values are to zero, the more the distribution is considered normal. Although there is inconsistency among scholars regarding the interpretation of skewness and kurtosis values (KIM, 2013; CURRAN et al., 1996) proposed a general guideline for evaluation. According to this guideline, absolute values greater than 2 for skewness and greater than 7 for kurtosis may indicate a significant departure from normality for a variable. By applying the critical value criterion of ±2.58 (HAIR et al., 2014), the results fall within the acceptable range, suggesting a normal distribution.

5.2 Validity and Reliability of the study

Once the data has been screened and confirmed for its normality, the subsequent stage involves assessing the construct reliability and validity of the research tool. These concepts, validity and reliability, are paramount in research methodology, mainly quantitative studies. Validity refers to how accurately a study measures its intended target. Essentially, it gauges whether the study effectively captures the phenomenon or construct it aims to examine. Study outcomes may be deceptive or incorrect without validity, resulting in flawed interpretations.

On the other hand, reliability concerns the consistency and steadfastness of measurement. It evaluates whether study outcomes can be reproduced or remain consistent over various conditions and time. A reliable measurement yields comparable results under consistent circumstances.

Conversely, an unreliable measurement may yield inconsistent or unpredictable results, hindering the ability to derive meaningful insights. Factor analysis explores interdependencies, aiming to uncover the inherent structure of measurement items (HAIR et al., 2014). This analytical technique comprises two main approaches: common factor analysis and component analysis. Its purpose is to assess the connections among multiple variables and express them in terms of shared underlying factors (HAIR et al., 2014). Through factor analysis, the goal is to condense a large set of associated items, which contribute to each construct, into a smaller set of factors while retaining as much information as possible. By scrutinizing the complex multi-component structure of a study variable, factor analysis identifies pertinent items commonly grouped into factors. This method offers an impartial foundation for creating composite measures by furnishing empirical estimates of the variable's structure (HAIR et al., 2014).

Consequently, factor analysis was employed to unveil the fundamental structure of the study variables' components and ascertain the minimal number of shared factors necessary to establish satisfactory relationships among the observed variables. Therefore, factor analysis is utilized in this study to demonstrate the primary patterns of factors that form the foundation of each study constructs, including innovation characteristics and TOE. It serves as an intermediary step to facilitate subsequent correlation and regression analyses. PCA was conducted on the 38 items representing independent research constructs to investigate the fundamental structure of the items in the study. Initially, the suitability and adequacy of the sample for factor analysis were evaluated by examining factors such as total variance explained, KMO measure, and commonalities.

5.2.1 Kaiser Meyer Olkin (KMO)

The KMO test assesses the suitability of the dataset for factor analysis by gauging the ratio of common variance among observed variables. KMO values range from 0 to 1. Values nearing 0 signify a scenario where partial correlations outweigh the sum of correlations, suggesting unsuitability for factor analysis (FIELD, 2009). Conversely, a value approaching 1 indicates tightly packed correlation patterns, promising distinct and dependable factors through factor analysis. FIELD (2009) recommends accepting KMO values above 0.5 as adequate, with values between 0.5 and 0.7 being mediocre, 0.7 and 0.8 good, 0.8 and 0.9 great, and above 0.9 superb. The KMO dimensions assessed the sampling adequacy for the items in the study instrument (refer to Table 9). The KMO measure, which indicates the suitability of the dataset for factor analysis, yielded a value of .771 for this set of variables.

Table 9. KMO and Bartlett's Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.771
Bartlett's Test of Sphericity	Approx. Chi-Square	3641.337
	df	741
	Sig.	.000

Source: Author's calculations using SPSS

Bartlett's sphericity test assesses the dataset's suitability for factor analysis by examining the interrelation among the observed variables. Essentially, it determines whether correlations among the variables justify grouping them under a common factor. A statistically significant level of Bartlett's test of sphericity, indicated by a significance value (sig.) below 0.50, suggests the presence of appropriate connections within the observed variables (HAIR et al., 2019). In Table 9, the Sig. value is shown as =.000. If the significance value is less than 5%, it indicates that the variance is met, while a value higher than 5% suggests that the variance is not met.

5.2.2 Communality

Communality quantifies how well the extracted factors clarify the data's variance. In simpler terms, it represents the total variance an original item shares with all other items in the study (HAIR et al., 2014). In other words, communalities show how much a variable contributes to the total variance the factor explains, indicating the degree of shared variance among variables included in the factor analysis. As per HAIR et al. (2019), a general guideline suggests that communalities of 0.4 or higher are adequate for retaining items, while those below 0.4 may necessitate a larger sample size. Nevertheless, higher communalities are typically preferred for most variables analyzed in factor analysis. Examining communality assists in identifying variables that are insufficiently explained by the factor solution, thereby not meeting acceptable explanation levels. Communality value is a helpful gauge for determining the variance in a specific variable attributed to the factor explanation. Lower communalities indicate that a considerable portion of the variable's variance remains unexplained by the factors.

In contrast, Greater commonalities suggest that the factor solution has captured a significant proportion of a variable's variance. As a rule of thumb, the factor solution should ideally account for at least half of each item's variance. Table 10 displays the extracted communality for the study items. The outcomes indicated that all communalities had met the 40% limit.

Table 10. Factors Communalities

Communalities			
Items	Extraction	Items	Extraction
GI1	.599	**MS4**	.639
GI2	.701	**TC1**	.676
GI3	.707	**TC2**	.610
MF1	.510	**TC3**	.771
MF2	.772	**C1**	.523
MF3	.644	**C2**	.726
CP1	.607	**C3**	.747
CP2	.581	**C4**	.652
CP3	.768	**RA1**	.760
CP4	.737	**RA2**	.561
VP1	.720	**RA3**	.727
VP2	.710	**RA4**	.712
VP3	.814	**RC1**	.685
MC1	.595	**RC2**	.671
MC2	.647	**RC3**	.731
MC3	.667	**AI1**	.776
MS1	.682	**AI2**	.798
MS2	.542	**AI3**	.822
MS3	.624	**AI4**	.796
Extraction Method: Principal Component Analysis.			

Source: Author's calculations using SPSS

5.2.3 Total Variance Explained

Determinating the number of extracted factors signifies the endpoint of dimension reduction, with various methods available for selection. These methods include considering factor eigenvalues greater than 1.0, evaluating the total variance explained by the factors, typically

60% or more, conducting a graphical assessment via the scree test, and opting for factors based on parallel analysis. Generally, a cumulative total variance extracted of around 50% or higher is often considered acceptable for exploratory purposes. Initially, an analysis was conducted to calculate eigenvalues for each component within the dataset. Eigenvalues, which denote the sum of squares of a factor, indicate the extent of variance accounted for by each factor (HAIR et al., 2019; HAIR et al., 2014). The Principal Component Analysis (PCA) outcomes revealed 11 factors derived from the diverse research constructs, each with eigenvalues surpassing Kaiser's criterion of 1. These factors collectively accounted for 68.44% of the variance, as detailed in Table 11. However, adhering to the principle of Interpretability, smaller factors were retained only if they held significant meaning. Additionally, the factors were retained for subsequent analysis due to the somewhat unclear convergence of the scree plot, which displayed slight inflexions.

Table 11. Total Variance Explained

Component	Initial Eigenvalues			Extraction Sums of Squared Loadings			Rotation Sums of Squared Loading[a]
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %	Total
1	9.204	24.220	24.220	9.204	24.220	24.220	5.132
2	3.146	8.278	32.498	3.146	8.278	32.498	4.733
3	2.241	5.898	38.397	2.241	5.898	38.397	4.548
4	2.111	5.556	43.953	2.111	5.556	43.953	5.015
5	1.699	4.471	48.424	1.699	4.471	48.424	5.768
6	1.451	3.819	52.243	1.451	3.819	52.243	4.065
7	1.397	3.678	55.921	1.397	3.678	55.921	3.423
8	1.265	3.328	59.249	1.265	3.328	59.249	2.869
9	1.227	3.229	62.477	1.227	3.229	62.477	3.943
10	1.184	3.116	65.593	1.184	3.116	65.593	3.097
11	1.082	2.848	68.442	1.082	2.848	68.442	1.586
12	.918	2.415	70.856				
……………………..							
38	.099	.261	100.000				
Extraction Method: Principal Component Analysis.							
a. When components are correlated, sums of squared loadings cannot be added to obtain a total variance.							

Source: Author's calculations

5.2.4 Factors Loading

Factor loading values indicate the extent of correlation between a variable and the extracted factor, with higher loadings suggesting a stronger correlation. As per the guidelines proposed by HAIR et al. (2019), absolute factor loading values of 0.3 are deemed significant, and a threshold of 0.4 is the minimum acceptable loading value to retain the variable. However, factor loadings of 0.5 are considered practically significant, while loadings of 0.7 or higher indicate a well-defined structure. Loadings indicate the magnitude and direction of the relationship between research variables and a discriminant function or a factor. PCA was performed using the Promax oblique rotation method with Kaiser Normalization. HAIR et al. (2014) suggest that scholars should always consider employing a nonorthogonal rotation method and evaluate its consistency with orthogonal outcomes.

Furthermore, oblique rotation is advised when an anticipated correlation between perceptual dimensions is present. Because Promax oblique rotation allows factors to be correlated, it is believed to produce superior outcomes compared to orthogonal rotation methods. With oblique rotation, two matrices are generated: the structure matrix and the pattern matrix. The pattern matrix, akin to the factor matrix in orthogonal rotation, displays the loadings on each factor. Conversely, the structure matrix examines the interrelation between factors. However, most scholars favour the pattern matrix for interpretation as it elucidates a variable's distinctive contribution to a factor. Appendix (4) presents the pattern matrix of the 11 extracted factors. However, items (GI1, MS3, MS4, C1) did not meet the 0.4 threshold; therefore, these items had to be eliminated.

5.3 Final Factor Analysis Interpretation

The following parts outline the primary categories of factors underpinning each study construct. These include Factor Analysis for the DOI, Factor Analysis for Organizational Capability, Factor Analysis of Managerial Capability, and Factor Analysis for the External Environment.

5.3.1 Factor Analysis: Innovation Attribute of AI

The innovation attributes of the AI concept, including complexity (RC), compatibility (C), and relative advantage (RA), were assessed using a total of 11 items. (See table 12) The KMO measures for the innovation traits construct items confirmed the suitability of the sample for factor analysis, with a KMO measure of sampling adequacy at .698.

Table 12. KMO and Bartlett's Test for Innovation Attribute of AI

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.698
Bartlett's Test of Sphericity	Approx. Chi-Square	475.322
	df	55
	Sig.	<.001

Source: Author’s calculations

Bartlett's sphericity test, indicating χ^2 (55) = 475.322, $p < .001$, indicated that item correlations were adequately high for Principal Component Analysis (PCA).

Factors were derived through PCA employing Promax rotation with Kaiser normalization, considering eigenvalues greater than 1. As depicted in Table 13, he outcome illustrates the variance explained, signifying the extraction of three factors for the innovation attribute of AI construct variables. The first factor, initially with 2.875 Sums of Squared Loadings and 2.498 post-rotation, contributes to 26.14% of the variance extraction, denoted as the "Compatibility" factor. The second factor, initially with 1.890 Sums of Squared Loadings and 1.813 post-rotation, accounts for 17.178% of variance extraction and is identified as the factor "Relative Advantage" factor. The third factor, initially with 1.583 Sums of Squared Loadings and 2.270 post-rotation, contributes to 14.394% of variance extraction, labelled as the ”Relative risk” factor. The cumulative variance extracted amounts to 57.712%, deemed suitable for subsequent statistical analysis.

Table 13.Variance Explained for Innovation Attribute of AI

Component	Initial Eigenvalues			Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings[a]
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %	Total
1	2.875	26.140	26.140	2.875	26.140	26.140	2.498
2	1.890	17.178	43.318	1.890	17.178	43.318	1.813
3	1.583	14.394	57.712	1.583	14.394	57.712	2.270
4	.882	8.014	65.727				
5	.793	7.210	72.937				
6	.678	6.165	79.102				
7	.576	5.233	84.336				
8	.507	4.613	88.949				
9	.462	4.201	93.150				
10	.420	3.822	96.972				
11	.333	3.028	100.000				
Extraction Method: Principal Component Analysis.							
a. When components are correlated, sums of squared loadings cannot be added to obtain a total variance.							

Source: Author’s calculations

Table 14 displays the communalities and Pattern Matrix for the Innovation Attribute of AI, encompassing instrument questions, items, communalities scores, and their loading pattern matrix. The loadings of the first factor varied between 0.402 for C1 and 0.846 for C3, surpassing the minimum threshold of 0.4. Similarly, communalities ranged from 40% to 76%, surpassing the defined minimum. For the second factor, the loadings ranged from 0.595 for RA1 to 0.808 for RA3, all surpassing the minimum. Additionally, communalities ranged between 59% and 80%, exceeding the defined minimum. In the third factor, the loadings ranged from 0.585 for RC1 to 0.807 for RC2, all surpassing the minimum threshold of 0.4. Additionally, communalities ranged between 40% and 65%.

Table 14. Communalities and Pettern Matrix and for Innovation Attribute of AI

Communalities			**Pattern Matrix[a]** Component		
Items	Initial	Extraction	1	2	3
C1	1.000	.404	.402		
C2	1.000	.601	.733		
C3	1.000	.670	.846		
C4	1.000	.601	.812		
RA1	1.000	.624		.595	
RA2	1.000	.548		.766	
RA3	1.000	.635		.808	
RA4	1.000	.612		.639	
RC1	1.000	.401			.585
RC2	1.000	.654			.807
RC3	1.000	.654			.801
Extraction Method: Principal Component Analysis. Rotation Method: Promax with Kaiser Normalization.					

Source: Author’s calculations

5.3.2 Factor Analysis: Organaizational Capabilty

The Organaizational Capabilty, including Managerial support (MS) and Technical capability (TC), were measured using a total of 7 items. (See table 15) The Kaiser-Meyer-Olkin (KMO) measures Organaizational Capabilty construct items confirmed the suitability of the sample for factor analysis, with a KMO measure of sampling adequacy at .809.

Table 15. KMO and Bartlett's Test for Organizational Capability

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.809
Bartlett's Test of Sphericity	Approx. Chi-Square	455.244
	df	21
	Sig.	<.001

Source: Author’s calculations

Bartlett's test, with χ^2 (21) = 455.244, p < .001, suggested that correlations between items were sufficiently high for Principal Component Analysis (PCA). Further, factors were derived through PCA employing Promax rotation with Kaiser normalization, considering eigenvalues greater than 1. As depicted in Table 16, the outcome illustrates the variance explained, signifying the extraction of one factor for organizational capability construct variables. The factor, initially with 3.461 Sums of Squared Loadings, contributes to 49.449 % of the variance extraction, denoted as the "Managerial support " factor.

Table 16.Variance Explained for Organizational Capability

Component	Initial Eigenvalues			Extraction Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	3.461	49.449	49.449	3.461	49.449	49.449
2	.952	13.598	63.047			
3	.769	10.985	74.032			
4	.670	9.570	83.601			
5	.475	6.782	90.384			
6	.405	5.792	96.175			
7	.268	3.825	100.000			
Extraction Method: Principal Component Analysis.						

Source: Author's calculations

Table 17 displays the communalities and Component Matrix for organizational capability, encompassing instrument questions, items, communalities scores, and their loading pattern matrix. The loadings of the factor varied between 0.613 for MS3 and 0.844 for TC3 after extracting one component with a communality of.376. Therefore, communalities ranged from 42% to 71%, reaching the defined minimum threshold of 40%.

Table 17. Communalities and Component Matrix and for Organizational Capability

Communalities			**Component Matrix[a]**
Items	Initial	Extraction	Component
MS1	1.000	.511	.715
MS2	1.000	.425	.652
MS3	1.000	.376	.613
MS4	1.000	.459	.677
TC1	1.000	.429	.655
TC2	1.000	.548	.741
TC3	1.000	.712	.844
Extraction Method: Principal Component Analysis. a. 1 components extracted.			

Source: Author's calculations

5.3.3 Factor Analysis: External Environment

The External Environment of the TOE, including Market uncertainty (MF), Government involvement (GI), Competitive pressure (CP), and Vendor partnership(VP), were assessed using a total of 13 items (Refer to table 18). The KMO measures for the innovation traits construct items confirmed the suitability of the sample for factor analysis, with a KMO measure of sampling adequacy at .754 Bartlett's test, with χ^2 (78) = 708.223, p < .001, suggested that correlations between items were sufficiently high for PCA analysis.

Table 18. KMO and Bartlett's Test for External Environment

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.754
Bartlett's Test of Sphericity	Approx. Chi-Square	708.223
	df	78
	Sig.	<.001

Source: Author's calculations using SPSS

Factors were derived through PCA employing Promax rotation with Kaiser normalization, considering eigenvalues greater than 1. As depicted in Table 19, the outcome illustrates the variance explained, signifying the extraction of three factors for External Environment construct variables.

Table 19.Variance Explained for External Environment

Component	Initial Eigenvalues			Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings[a]
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %	Total
1	3.948	30.370	30.370	3.948	30.370	30.370	2.899
2	1.808	13.909	44.279	1.808	13.909	44.279	2.823
3	1.386	10.664	54.943	1.386	10.664	54.943	2.548
4	.977	7.516	62.459				
5	.821	6.318	68.777				
6	.779	5.993	74.769				
7	.694	5.341	80.110				
8	.599	4.611	84.721				
9	.536	4.123	88.844				
10	.461	3.548	92.392				
11	.417	3.209	95.601				
12	.298	2.294	97.895				
13	.274	2.105	100.000				
Extraction Method: Principal Component Analysis.							
a. When components are correlated, sums of squared loadings cannot be added to obtain a total variance.							

Source: Author's calculations

The first factor, initially with 3.948 Sums of Squared Loadings and 2.899 post-rotation, contributes to 30.37% of the variance extraction, denoted as the "Government Involvement" factor. The second factor, initially with 1.808 Sums of Squared Loadings and 2.823 post-rotation, accounts for 13.909% of variance extraction, identified as the "Market uncertainty" factor. Lastly, the third factor, initially with 1.386 Sums of Squared Loadings and 2.548 post-rotation, contributes 10.664% of variance extraction, labeled as the ”Competitive pressure” factor. The cumulative variance extracted amounts to 54.943%, suitable for subsequent statistical analysis.

Table 20 displays the communalities and Pattern Matrix for the External Environment, encompassing instrument questions, items, communalities scores, and their loading pattern matrix. The loadings of the first factor varied between 0.806 for VP1 and 0.862 for VP2, reaching the minimum threshold of 0.4. Similarly, communalities ranged from 61% to 70%, surpassing the defined minimum. For the second factor, the loadings ranged from 0.406 for GI1 to 0.724 for MF1, surpassing the minimum. Additionally, communalities ranged between 40% and 43%, exceeding the defined minimum. In the third factor, the loadings ranged from 0.506 for CP1 to 0.866 for CP4, surpassing the minimum. Additionally, communalities ranged between 50% and 70%, exceeding the defined minimum.

Table 20. Communalities and Pettern Matrix and for External Environment

Communalities			**Pattern Matrix[a]** Component		
	Initial	Extraction	1	2	3
GI1	1.000	.402		.406	
GI2	1.000	.449		.534	
GI3	1.000	.419		.465	
MF1	1.000	.439		.724	
MF2	1.000	.535		.721	
MF3	1.000	.501		.673	
CP1	1.000	.506			.506
CP2	1.000	.534			.565
CP3	1.000	.726			.849
CP4	1.000	.702			.866
VP1	1.000	.618	.806		
VP2	1.000	.704	.862		
VP3	1.000	.736	.809		
Extraction Method: Principal Component Analysis. Rotation Method: Promax with Kaiser Normalization.					

Source: Author’s calculations

5.4 Reliability Measure

Reliability refers to evaluating the consistency and homogeneity of scale measures and determining how well multiple variable measurements align with each other (HAIR et al., 2014). It assesses whether questionnaire items consistently reflect the constructs they are meant to measure, thereby supporting the generalizability of study results. Researchers commonly employ two primary measures to establish instrument reliability. First, they examine each item's correlation with the scale's total score and the inter-item correlation, aiming for correlations exceeding 0.5 (HAIR et al., 2014). Second, Cronbach's alpha is commonly employed to assess the overall scale consistency. Cronbach's alpha measures the extent to which respondents consistently answer all items representing a scale or variable, with its formula provided by FIELD (2009).

$$\alpha = \frac{N.\bar{c}}{\bar{v}+(N-1).\bar{c}}$$ ……………………………………………………. FIELD (2009).

Cronbach's alpha indicates reliability on a scale of 0 to 1, with values between 0.60 and 0.70 considered the minimum acceptable threshold (Hair et al., 2014). As shown in Table 21, the reliability measures Cronbach's alpha for the study items indicates values ranging from the highest of 0.897 to the lowest of 0.880. The overall alpha value for all variables is 0.888, demonstrating good internal consistency across the research scale. These results confirm the assumed reliability of the research instrument. The analysis confirms the reliability and validity of the study instrument, revealing stability and internal consistency among all questionnaire items. The Cronbach alpha coefficient value also suggests internal consistency among the questionnaire items.

Table 21.Cronbach's alpha coefficient

Item	Cronbach's Alpha	N of Items
Government involvement (GI)	.886	3
Market factors uncertainty (MF)	.887	3
Competitive pressure (CP)	.887	4
Vendor partnership (VP)	.883	3
Managerial capability (MC)	.886	3
Managerial support (MS)	.884	4
Technical capability (TC)	.881	3
Compatibility (C)	.885	4
Relative advantage (RA)	.885	4
Relative risk (RC)	.895	3
AI adoption (AI)	.828	4
Total	**.888**	

Source: Author's calculation

5.5 Testing the Study Hypotheses

In this part, the study identifies factors and associated variables that are believed to predict relationships. Initially, it analyzes the relationships at the level of two constructs: Managerial capability with the Innovation aspect of AI and Managerial capability with organizational capability. Subsequently, it focuses on the primary predictive relationships outlined in the research framework (refer to Figure 3), which illustrate connections between the research constructs and the adoption of AI within companies.

The study utilizes multiple regression analysis to achieve its objective, a statistical method for examining how one predicted variable is linked to several independent predictors. The goal is to use the values of independent variables to forecast a single dependent variable, thereby addressing the study queries. Each independent variable is given a coefficient in regression analysis to enhance its predictive performance. Also, each independent variable is assigned a weight to optimize its predictive capability. As HAIR et al. (2014) noted, regression is a valuable analytical tool extensively utilized in business decision-making research, applicable to general and specific issues. It is the foundation for developing business forecasting models, ranging from micro-level firm analysis to macroeconomic assessments. Additionally, the literature indicates the widespread and intensive utilization of regression in research on technology adoption. Hence, this study will employ multiple regression analysis to address the study questions and achieve the stated goals.

The multiple regression analysis is conducted on two levels: the broader main research constructs level and the inner-construct level. Initially, it explores the anticipated relationships within the Innovation attributes of the AI construct. Next, it investigates the hypothesized relationships within the organizational capability construct. Finally, it tests the presumed relationships between the independent variables of the leading research conceptual framework and the dependent variable, AI Adoption.

5.5.1 Multiple Regression for The Innovation Attribute of AI

Multiple regression analysis was conducted to evaluate the relationship between the predictors of Managerial capability (MC) and the anticipated dependent variable, the Innovation attribute of AI, which includes complexity (RC), compatibility (C), and relative advantage (RA). Table 22 shows that Relative Advantage appears to have a significant positive relationship with Managerial Capability. The positive sign of the standardized coefficient .211 indicates a positive relationship between Managerial Capability and Relative Advantage. In other words, as Managerial Capability increases, the Relative Advantage of AI tends to increase as well. In this case, a coefficient of .211 indicates a moderate positive relationship between the two variables. Also, The p-value associated with the coefficient is .001, indicating that the relationship between Managerial Capability and Relative Advantage is statistically significant. Complexity appears to have a significant negative relation with Managerial Capability. The negative sign of the standardized coefficient -.295 indicates a negative relationship between Complexity and Managerial Capability. In other words, as the Complexity of AI increases, the Managerial Capability tends to decrease. The magnitude of the coefficient indicates the strength of the relationship between Complexity and Managerial Capability. Since the coefficient is negative, it suggests that higher levels of Complexity are associated with lower levels of Managerial Capability. The strength of the relationship increases as the coefficient approaches -1 or 1.

The p-value associated with the coefficient indicates its statistical significance. A p-value of less than .001 indicates that the relationship between complexity and managerial capability is statistically significant. Compatibility appears to be significantly and positively related to managerial capability. A more significant coefficient suggests a stronger relationship. In this case, a coefficient of .350 indicates a moderate positive relationship between Managerial Capability and Compatibility. Further, the p-value associated with the coefficient is less than .001, indicating that the relationship between Managerial Capability and Compatibility is statistically significant.

Table 22. Predictors of the Innovation Attribute of AI Coefficients[a]

Model factors	Unstandardized Coefficients		Standardized Coefficients	t	Sig.
	B	Std. Error	Beta		
Relative Advantage	.148	.045	.211	3.300	.001
Complexity	-.228	.047	-.295	-4.816	<.001
Compatibility	.227	.042	.350	5.459	<.001
a. Dependent Variable: Managerial Capability					

Source: Author's caluculation

Furthermore, Table 23 displays the outcomes of the Model Summary for the Innovation Attribute of AI, indicating that the R-squared of predictors is .312, suggesting that these factors can account for 31.2% of the variation in Managerial Capability. Notably, among the predictors, Compatibility emerges as the most significant predictor of Managerial Capability.

Table 23. Predictors of the Innovation attribute of AI Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.559[a]	.312	.301	1.68737
a. Predictors: (Constant), Compatibility, Relative risk /Complexity, Relative Advantage				

Source: Author's calculation

Additionally, in Table 24, the ANOVA results reveal a significant overall model fit for the regression model predicting the Innovation Attribute of AI, represented by Managerial Capability. The F-ratio value of 28.316, coupled with a highly significant p-value of less than 0.001, indicates that the predictors in the model (including Compatibility, Relative risk/Complexity and Relative Advantage) collectively contribute significantly to explaining the variation in Managerial Capability.

Table 24. Predictors of the Innovation Attribute of AI ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	241.863	3	80.621	28.316	<.001[b]
	Residual	532.430	187	2.847		
	Total	774.293	190			
a. Dependent Variable: Managerial Capability						
b. Predictors: (Constant), Compatibility, Relative risk/Complexity, Relative Advantage						

Source: Author's caluculation

5.5.2 Multiple Regression for Organizational Capability

Multiple regression analysis was conducted to evaluate the relationship between managerial capability (MC) predictors and the predicted dependent variable of organaizational capabilty. Table 25 displays the relationship between Managerial Capability and Managerial Support; the positive sign of the standardized coefficient .189 indicates a positive relationship between Managerial Capability and Managerial Support. In other words, as Managerial Capability increases, so does Managerial Support. In this case, a coefficient of .189 indicates a relatively weak positive relationship between the Managerial Capability and Managerial Support. The p-value is .012, less than the significance level of .05. This indicates that the relationship between Managerial Capability and Managerial Support is statistically significant. Still the significance level is not very high.

Further, the positive sign of the standardized coefficient .420 indicates a relatively strong positive relationship between Managerial Capability and Technical Capability. In other words, as Managerial Capability increases, Technical Capability also tends to increase. Further, the p-value associated with the coefficient is less than .001, indicating that the relationship between Managerial Capability and Technical Capability is statistically significant at a very high confidence level.

Table 25. Predictors of the Organizational Capability Coefficients[a]

Model	Unstandardized Coefficients		Standardized Coefficients	t	Sig.
	B	Std. Error	Beta		
Managerial Support	.119	.047	.189	2.525	.012
Technical Capability	.275	.049	.420	5.607	<.001
a. Dependent Variable: Managerial Capability					

Source:Author's caluculation

Furthermore, Table 26 displays the outcomes of the model summary for the regression analysis of the organaization capabilty, indicating that the R-squared of predictors is .304, suggesting that these factors can account for 30.4% of the variation in Managerial Capability. Among the predictors, Technical Capability emerges as the most significant predictor of Managerial Capability.

Also, in Table 27, The ANOVA results reveal a significant overall model fit for the regression model predicting the organaizational capabilty, represented by managerial capability. The F-ratio value of 41.128, coupled with a highly significant p-value of less than 0.001, indicates that the predictors in the model collectively contribute significantly to explaining the variation in Managerial Capability.

Table 26. Predictors of the Organizational Capability Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.552[a]	.304	.297	1.69264
a. Predictors: (Constant), Technical Capability, Managerial Support				

Source:Author's caluculation

Table 27. Predictors of the Organizational Capability ANOVAa

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	235.668	2	117.834	41.128	<.001[b]
	Residual	538.625	188	2.865		
	Total	774.293	190			
a. Dependent Variable: Managerial Capability						
b. Predictors: (Constant), Technical Capability, Managerial Support						

Source:Author's caluculation

5.5.3 Multiple Regression for AI Adoption in Firms

Multiple regression analysis was conducted to evaluate the relationship between the predictors of AI innovation attribute, organaizational capabilty, external environment and the predicted dependent variable of AI Adoption (refer to Table 28). The positive sign of the standardized coefficient .085 suggesting a positive association between Relative Advantage and AI Adoption. However, the magnitude of the coefficient is relatively small , which suggests a weaker relationship. In this case, a coefficient of .085 indicates a relatively weak positive relationship between the Relative Advantage and AI Adoption. The p-value associated with the coefficient is .241, more significant than the significance level of .05. This suggests that the relationship between Relative Advantage and AI Adoption is not statistically significant.

Table 28. Predictors of the AI Adoption Coefficientsa

Model	Unstandardized Coefficients		Standardized Coefficients	t	Sig.
	B	Std. Error	Beta		
Relative Advantage	.091	.077	.085	1.176	.241
Relative risk/ Complexity	.106	.074	.090	1.427	.155
Compatibility	.129	.071	.130	1.819	.070
Managerial Support	.160	.076	.163	1.794	.029
Technical Capability	.307	.080	.308	3.836	<.001
Government Involvement	-.029	.087	-.024	-.336	.738
Market Uncertainty	-.332	.094	-.234	-3.533	<.001
Competitive Pressure	.177	.071	.165	2.492	.014
Vendor Partnership	.261	.083	.240	3.135	.002
a. Dependent Variable: AI Adoption					

Source:Author's caluculation

Further, the standardized coefficient .090 indicates a weak positive association between Complexity and AI Adoption. The p-value .155 is more significant .05, indicating that the relationship is not statistically significant. For the Compatibility factor, the positive sign of the standardized coefficient .130 suggests a relatively weak positive association between Compatibility and AI Adoption. The p-value is .070, which is greater than significance level of .05. While the relationship between Compatibility and AI Adoption shows a trend toward significance, it is not statistically significant. For Managerial Support, the positive sign of the standardized coefficient .163 suggests a positive association between Managerial Support and AI Adoption. The p-value associated with the coefficient is .029, which indicates that the relationship between managerial support and AI adoption is statistically significant. For Technical Capability, The positive sign of the standardized coefficient .308 suggests a moderate positive association between Technical Capability and AI Adoption. The p-value associated with the coefficient is less than .001, indicating that the relationship between Technical Capability and AI Adoption is statistically significant at a very high confidence level.

For Government Involvement, the negative sign of the standardized coefficient -.024 suggests a fragile negative association between Government Involvement and AI Adoption. The p-value is .738, which is much more significance level of .05. This indicates that the relationship between Government Involvement and AI Adoption is not statistically significant. In the case of Market Uncertainty, The negative sign of the standardized coefficient -.234 suggests a moderate negative association between Market Uncertainty and AI Adoption. The p-value is less than .001, indicating that the relationship between Market Uncertainty and AI Adoption is statistically significant at a very high confidence level. For Competitive pressure, the positive sign of the standardized coefficient .165 suggests a moderate positive association between Competitive Pressure and AI Adoption. The p-value is .014, less than the conventional significance level. This indicates that the relationship between Competitive Pressure and AI Adoption is statistically significant at the 0.05 level. The positive sign of the standardized coefficient .240 suggest a moderate positive relationship between Vendor Partnership and AI Adoption. The p-value is .002, which is less than the conventional significance. This indicates that the relationship between Vendor Partnership and AI Adoption is statistically significant.

Furthermore, Table 29 displays the outcomes of the AI adoption model summary, indicating that the R-squared of predictors is .414, suggesting that these factors can account for 41.4% of the total variation in AI adoption.

Table 29. Predictors of the AI Adoption Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.643[a]	.414	.385	2.41035
a. Predictors: (Constant), Vendor Partnership, Competitive Pressure, Relative risk/Complexity, Compatibility, Market Uncertainty, Relative Advantage, Government Involvement, Managerial Support, Technical Capability				

Source:Author's caluculation

Also, in Table 30, the ANOVA test results reveal a significant overall model fit for the regression model. The F-ratio value of 14.190 and a highly significant p-value of less than 0.001.

Table 30. Predictors of the AI Adoption ANOVAa

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	741.977	9	82.442	14.190	<.001[b]
	Residual	1051.573	181	5.810		
	Total	1793.550	190			
a. Dependent Variable: AI Adoption						
b. Predictors: (Constant), Vendor Partnership, Competitive Pressure, Relative risk Complexity, Compatibility, Market Uncertainty, Relative Advantage, Government Involvement, Managerial Support, Technical Capability						

Source:Author's caluculation

This section outlines the outcomes of hypothesis testing to assess the connections between different factors and the integration of artificial intelligence within telecommunication firms. The hypotheses derived from the literature review were tested using multiple regression analysis, which allowed for the assessment of the strength and significance of these relationships.

Table 31 shows a summary of the results obtained after testing each hypothesis, including the coefficients, significance levels, and interpretations of the findings in the previous section. To conclude, Hypotheses H1.2, H1.3, and H4.1 have been rejected. Meanwhile, hypotheses H3.1, H3.2, H3.3, H3.4, H3.5, H2.1, H2.2, H4.2, H4.3, and H4.4 have been accepted. Furthermore, hypothesis H1.1 was partially accepted.

Table 31. Results Summary of Hypotheses Test *Attributes*

Hypotheses	Results
1. Innovation attribute of AI	
H1.1: Compatibility is significantly associated with AI adoption.	**Partially supported**
H1.2: Relative advantage is significantly associated with AI adoption.	**Rejected**
H1.3: Complexity affects AI adoption negatively.	**Rejected**
2. Managerial capability	
H3.1: Managerial capabilities affect the compatibility of AI positively.	**Supported**
H3.2: Managerial capabilities positively affect the relative advantage of AI.	**Supported**
H3.3: Managerial capabilities affect the complexity of AI negatively.	**Supported**
H3.4: Managerial capabilities influence the managerial support positively.	**Supported**
H3.5: Managerial capabilities are positively associated with technical capabilities.	**Supported**
3. Organizational capability	
H2.1: Managerial support positively affect AI adoption.	**Supported**
H2.2: Technical capabilities are positively effect to AI adoption.	**Supported**
4. External environment	
H4.1: Government involvement is positively associated with AI adoption.	**Rejected**
H4.2: Competitive pressure is positively influencing AI adoption.	**Supported**
H4.3: Market uncertainty is negatively associated with AI adoption.	**Supported**
H4.4: Vendor partnership is positively associated with AI adoption.	**Supported**

Source: Author's Creation (2024)

5.6 Discussion of Mean Values

This section will present the mean values of the research factors. To. To achieve this, a three-level classification has been devised based on the mean values, employing a weighted approach with a Category Range of 2. This method creates a three-level scale, facilitating analysis, improving interpretability, enabling comparison, and enhancing research findings' practical application and communication.

Category Range = (Maximum weight (7) – lowest weight (1)) / Number of levels (3) = 2

1 – less than or equal 3 Low

> 3 – less than or equal 5 Moderate

> 5 – less than or equal to 7 High

A comprehensive view of the mean responses indicates that the research indicators generally surpassed the median of 4 (refer to Table 8). Additionally, Figure 7 shows the mean for each variable and the standard deviation. Hence, this leads to various conclusions regarding how the study sample perceives each measured variable within each construct. For example, within the Innovation Attribute of the AI construct, the highest mean value of 5.72 was observed for the RA factor, suggesting that leaders perceive a significant advantage resulting from AI adoption in firms. Similarly, in the Organizational Capability factor construct, the respondents are more positively inclined toward the gained Managerial support (MS) with a mean value of 5.38, suggesting that Managerial support holds a significant advantage in AI adoption within firms.

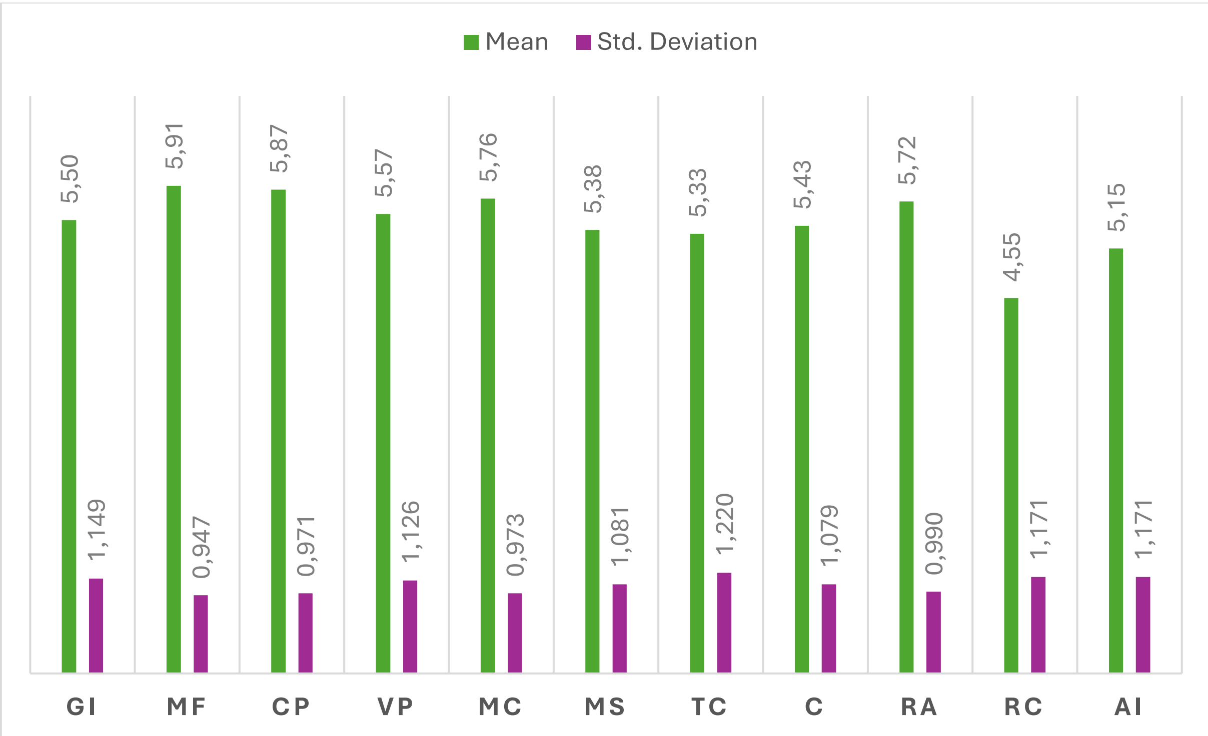

Figure 7. Mean and Standard Deviation

Source: Author's Creation

Considering the mean values of the responses for the External Environment, the outcomes of the four-factor predictors (including Government involvement (GI), Market uncertainty (MF), Competitive pressure (CP), and Vendor partnership (VP)) showed high mean values. The Market uncertainty factor had the highest mean value of 5.91, suggesting that respondents perceive market uncertainty to have a negative impact on AI adoption applications. Tthe lowest mean value was 5.5, suggesting that government involvement affects AI adoption through regulations and policies.

Among the variables, the lowest mean value was 4.55 for Relative risk/complexity, indicating a moderate perception of its impact on AI application complexity and AI adoption within firms.

The mean value of 5.15 for the dependent variable, AI adoption, reflects a significantly high mean, implying that leaders hold a strongly positive attitude toward implementing AI techniques within their companies.

Furthermore, response variability should be considered by examining the standard deviation. A higher standard deviation indicates more responses variability, while a lower standard deviation suggests greater agreement among respondents. The highest standard deviation in the technical capability variable indicates more responses variability. Meanwhile, Market Uncertainty has the lowest standard deviation, indicating greater agreement among respondents.

Moreover, the standard deviation and the mean of the research questions are displayed in Table 8. For example, MF3 ‘AI has the potential to enhance the company's competitive edge’. It has a mean of 5.98, reflecting a significantly high mean. This suggests that respondents agreed that AI could help their company gain competitiveness, with a standard deviation of 0.891 indicating greater agreement among respondents. AI has the potential to enhance the company's competitive edge.

The CP4 has a mean of 6.01, reflecting a significantly high mean. This indicates that participants strongly agreed that there is significant competition regarding the quality of products or services, with a standard deviation of 0.846 indicating greater agreement among respondents.

The MC2 and MC3 have means of 5.77 and 6.11, respectively, reflecting significantly high means. This suggests that respondents strongly agreed that inter-department cooperation and communication are essential for adopting AI technologies, with standard deviations of 0.887 and 0.836, respectively, indicating greater agreement among respondents.

Additionally, TC2 ’we can swiftly incorporate new AI technologies into our current infrastructure’ and RC1 ’Adopting AI innovation lacks application maturity’ have the lowest values of 4.92 and 3.81, respectively, reflecting a moderate mean. Furthermore, the standard deviation of 1.432 and 1.304 indicates more variability among respondents.

5.7 Discussion

The telecommunications sector faces intense competition, compelling operators to enhance service quality, innovate products, and lower service fees to sustain market share and competitiveness. Integrating AI presents opportunities for operators to develop novel profit models. Moreover, prioritizing factors crucial for long-term company growth can aid operators in overcoming challenges and fostering sustainability. This study explore the factors influencing AI adoption within firms, aiming to delineate the most influential Factor. Additionally, it endeavors to outline managerial strategies conducive to enhancing AI adoption and fostering seamless integration with human intelligence by employing a comprehensive model that integrates the attributes of AI innovation with environmental and organizational factors.

In the telecommunications sector, AI applications are increasingly aiding operators in the optimizating, managing and maintaning infrastructure, alongside customer support operations. Critical AI applications embraced by telecom operators encompass customer service chatbots, Voice Assistants, Intelligent Network Management, and Build AI platforms. According to survey findings, 40.8% of respondents anticipate prioritizing AI technologies for Intelligent Network Management, with 20.9% considering AI chatbots, 18.8% planning to develop AI platforms, 14.7% aiming to adopt AI voice assistants, and 4.7% exploring other categories such as Customer Relationship Management (CRM) and Virtual Network Functions (VNFs). While telecom operators in Hungary have initiated AI deployments, the utilization of AI in communication remains at a nascent stage.

The primary results of the research indicate six factors directly impact AI adoption: Compatibility, Technical capabilities, Managerial Support, Competitive pressure, Market uncertainty, and Vendor partnership. Additionally, the findings suggest that managerial capability affects other organizational capabilities and the innovation attributes of AI, indicating an indirect relationship between managerial capability and AI adoption.

Regarding the DOI, compatibility is observed to have a positive correlation with AI adoption. This discovery aligns with findings from prior research documented in the literature review (e.g., WANG et al., 2010; CHEN, 2019; THONG, 1999; CHONG et al., 2009). Compatibility exhibits the strongest association with AI adoption compared to other innovation attributes of AI, namely relative advantage and complexity. This suggests that companies prioritize the compatibility of AI over other factors outlined in the DOI theory, highlighting its significance. The study reveals that 40.8% of respondents anticipate the initial adoption of Intelligent

Network Management technology, indicating a high likelihood of adoption within the telecom industry.

Consequently, ensuring compatibility between AI and existing network infrastructure is critical concern for telecom operators. Previous research by OLIVEIRA et al. (2014) suggests that compatibility is an enabler for the adopting cloud computing in the service industry but not in manufacturing. They attribute this difference to variances in Internet-based business operations and work style preferences between the service and manufacturing sectors. Given that telecom falls within the service sector, the findings regarding compatibility in this research align with those of OLIVEIRA et al. (2014) and CHEN (2019).

Relative advantage (H1.2) exhibits a weak and statistically insignificant association with AI adoption, indicating that organizations may lack trust in or remain uncertain about the benefits of AI technologies and their applications. This finding aligns with the results of the study by ROBINSON (2019), which also noted a lack of trust or relative advantage in AI, particularly in intuitive autonomous intelligence tasks like human contact and interviewing.

Complexity (H1.3) is not identified as a hindrance to AI adoption. This contrasts with various studies on IT adoption determinants, such as HRIS (TEO et al., 2007), eHR (WICKRAMASINGHE, 2010), and cloud computing (LOW et al., 2011; OLIVEIRA et al., 2014), and but business intelligence (SUJITPARAPITAYA et al., 2012), which also did not find a significant relationship between complexity and IT adoption, consistent with the findings of this study.

Thesis 1. There are significant statistical relationships between the innovation attributes of AI and AI adoption in telecommunications companies. Relative advantage shows a weak positive association with AI adoption, but the relationship is not statistically significant, reflecting limited influence on adoption decisions. Similarly, complexity demonstrates a weak positive relationship with AI adoption, but this too is statistically insignificant, indicating minimal impact. Also, compatibility shows weak positive association with AI adoption, and the relationship trends toward significance it does not reach the threshold for statistical significance.

Regarding organizational capabilities, the results of the research deliver empirical support for the notion that managerial support (H2.1) catalyses AI adoption. Leaders are crucial in promoting AI adoption by actively participating in the process and effectively coordinating organizational resources. Additionally, top managers are instrumental in setting the employees's mission, policies, vision, and direction, thus facilitating the successful implementation of IS projects (TRAVAGLIONE et al., 2017). For successful AI adoption, it is essential that top leaders within a ompany harness AI applications as a strategic core competency. This outcome resonates with earlier research on the adoption and utilization of innovative technologies (CHEN, 2019; WANG et al., 2010; CHONG et al., 2009; OLIVEIRA et al., 2014).

Technical capabilities show a positive correlation with AI adoption (H2.2). Technical capabilities demonstrate the strongest association with AI adoption among the factors examined. A robust technical capability minimizes integration complexities, streamlining the adoption process of AI systems by the IT team. The successful integration of AI applications relies on a company's ability to meet technological objectives and seamlessly incorporate AI technologies into its existing infrastructure. The proficiency with which a company integrates emerging AI technologies within its IT framework directly impacts its capacity to reduce expenses and effectively allocate resources for profitable adoption. These results align with prior research, which suggests that technical competencies support the adoption of information technology. (e.g., OLIVEIRA et al., 2014; GARRISON et al., 2015).

Thesis 2. Organizational capability significantly influences AI adoption in telecommunications companies. Managerial support demonstrates a statistically significant positive relationship with AI adoption, acting as a catalyst by fostering leadership involvement and effective resource coordination. Leaders play a critical role in driving adoption by actively participating in the process and aligning organizational efforts. Similarly, technical capability shows a statistically significant moderate positive association with AI adoption, emphasizing its importance in enabling organizations to integrate AI solutions effectively. These findings highlight the pivotal roles of managerial support and technical capability in shaping AI adoption outcomes.

Managerial capability is strongly associated with the innovation attributes of AI and organizational capabilities (H3.1, H3.2, H3.3, H3.4, H3.5). Consequently, managerial capability indirectly influences AI adoption. Enhanced managerial capability correlates with heightened managerial support and technical capability, promoting greater compatibility in AI implementation, fostering a relative advantage of AI application benefits, and mitigating perceived complexities. While superior managerial capability is associated with increased AI adoption, it does not directly impact adoption. Instead, company' managerial capability influences AI adoption indirectly through managerial support and AI innovation attributes, which is supported by (CHEN, 2019; GARRISON et al., 2015; WIXOM & WATSON, 2001). GARRISON et al. (2015) stated that managerial capability encompasses intangible assets significantly impacting IT adoption. According to research (EMMELHAINZ, 1988), organizational resistance to change is the primary obstacle delaying the adoption of IT. WIXOM and WATSON (2001) noted that effective managerial capabilities are demonstrated through clearly defined strategic plans and objectives, streamlined internal communication and collaboration, and comprehensive training and development initiatives within the organization. Businesses with powerful managerial capability can swiftly overcome such barriers and readily embrace modern technologies.

Thesis 3. Managerial capability is strongly associated with both the innovation attributes of AI and organizational capabilities, indirectly influencing AI adoption in telecommunications companies. Compatibility emerges as the most critical innovation attribute, showing a strong, statistically significant positive relationship with managerial capability, highlighting its role in aligning AI solutions with existing systems. Technical capability demonstrates a relatively strong and statistically significant positive association with managerial capability, further emphasizing its importance in facilitating AI adoption. In contrast, managerial support shows a weaker but statistically significant positive relationship with managerial capability, highlighting its role as a complementary factor. While relative advantage has a weaker positive association, reflecting uncertainty about AI's benefits, complexity demonstrates a negative relationship but does not act as a major barrier to adoption.

Regarding the external environment, government involvement shows a weak negative relationship that affects AI adoption (H4.1). Governments can formulate supportive plans and policies to encourage the commercialization of emerging technologies and establish regulations conducive to technological development. STOICA et al. (2005) emphasized the significance of government frameworks in shaping the adoption of new technologies, recognizing it as a multifaceted process. Furthermore, government involvement can negatively affect AI adoption through regulatory barriers, uncertainty, lack of support, privacy and security concerns, and ethical and social implications. These factors can create obstacles for businesses, making investing in and deploying AI technologies effectively challenging. Balancing regulation and support is essential for maximizing the advantages of AI adoption while addressing potential risks and challenges.

Competitive pressure is positively associated with AI adoption (H4.2). This aligns with PREMKUMAR and RAMAMURTHY (1995), who underscored adopting new technologies as a strategic imperative amid intense competition. Competitive pressure stimulates technological innovation. Embracing modern technology frequently becomes a strategic imperative for staying competitive (NOVAKOVA, 2020; SCHWAB, 2017; SUMNER, 2000). MANSFIELD et al. (1977) discovered that intense market competition hastens the swift dissemination of IT innovations. For example, LOW et al. (2011) found in their study that competitive pressure and pressure from trading partners had a notable impact on the utilization of cloud computing. Similarly, research on e-business adoption (LIN & LIN, 2008; OLIVEIRA & MARTINS, 2011) and business intelligence adoption (BHATIASEVI & NAGLIS, 2018) has yielded varying results regarding the influence of competitive pressure.

Market uncertainty is negatively associated with AI adoption (H4.3). Market uncertainty embodies the unpredictability and lack of clarity inherent in commercial markets, presenting challenges for businesses in making well-informed decisions and strategizing for the future. In any commercial market, uncertainties abound, presenting a mix of risks and opportunities. Those skilled at identifying opportunities amidst market volatility stand to gain competitive advantages. Market uncertainty significantly impacts the adopting of artificial intelligence (GANS, 2023). Hence, companies postpone AI implementation due to their inclination to avoid risks, difficulties in allocating resources, struggles with long-term planning, uncertainties regarding regulations, and concerns about the potential adoption failure.

Furthermore, the research indicates a positive correlation between vendor partnership and AI adoption (H4.4). Collaborating with partners significantly facilitates the adoption of AI. Vendors are essential participants in the AI domain, providing internal expertise and resources that firms may lack for innovations like AI applications. Developing AI independently demands substantial investment and specialized talent. Additionally, vendors rely on data from their clients. Therefore, partnering with AI vendors is advisable for firms implementing AI applications effectively. The right vendor can streamline cooperation and ensure the partnership enhances the company's competitive edge.

Thesis 4. The external environment significantly influences leaders' attitudes toward AI adoption in telecommunications companies. Competitive pressure and vendor partnerships emerge as positive drivers, with both demonstrating statistically significant moderate positive relationships with AI adoption. Conversely, market uncertainty shows a statistically significant moderate negative association with AI adoption, reflecting the challenges posed by unpredictable market conditions. Government involvement, however, exhibits a fragile negative association with AI adoption and is not statistically significant, indicating limited or inconsistent influence.

Consequently, firms should establish partnerships and resource-sharing networks to meet market demands better and gain a competitive edge. Enhancing vendor relationships through communication and collaboration can ultimately reduce the organisation's cost (FINDIKOGLU et al., 2021). According to ASSAEL (1984), vendor involvement can significantly affect the rate of diffusion and adoption of new products. The result in this study aligns with OLIVEIRA and MARTINS (2010), indicating that collaboration with trading partners significantly facilitates innovation adoption, particularly in the tourism and telecom sectors. Empirical data further validates the importance of vendor partnerships as a key factor in driving innovation adoption, as evidenced by research conducted by SULAIMAN and WICKRAMASINGHE (2014), YANG and KANKANHALLI (2013), and AHMADI et al. (2015).

To conclude, the findings validate the suggested model concerning the fundamental factors contributing to the successful adoption of AI. These factors encompass the organizational capability, DOI, and the external environment. The results affirm the significance of these factors in IT adoption, with managerial capability emerging as an indirect yet positively associated factor influencing AI adoption. Furthermore, the effectiveness of the TOE in analyzing the success factors of AI adoption is demonstrated by the findings.

6. CONCLUSION AND RECOMMENDATIONS

This chapter offers the study conclusions and recommendations, aligning with the defined research goals and providing insights into the research question based on the findings.

6.1 Conclusion

This study aims to investigate the factors influencing AI adoption within firms, focusing on identifying the most influential factors and outlining managerial strategies to enhance adoption and integration with human intelligence. The Hungarian telecommunications industry was selected as the research sample, comprising 269 companies. The number of valid responses for analysis is 191. Within the telecommunications sector, AI applications are increasingly aiding operators in optimizing infrastructure management, customer support operations, and innovation. Key applications include customer service chatbots, Voice Assistants, Intelligent Network Management, and Build AI platforms. Despite the initiation of AI deployments by telecom operators in Hungary, AI's utilization in communication remains nascent.

The primary findings of this study identify six factors directly impacting AI adoption: Compatibility, Technical capabilities, Managerial Support, Competitive pressure, Market uncertainty, and Vendor partnership. Additionally, managerial capability indirectly influences AI adoption, indicating the crucial role of effective management in promoting the adoption and coordination of organizational resources. Figure 8 presents a comprehensive review of the study model, with accepted research hypotheses highlighted in black.

In terms of AI innovation attributes, compatibility emerges as a critical factor positively associated with AI adoption, emphasizing the importance of aligning AI with existing network infrastructure. Relative advantage exhibits a weak correlation with AI adoption, indicating uncertainty about the benefits of AI technologies. Complexity does not hinder AI adoption significantly, contrasting with findings in other IT adoption studies.

Regarding organizational capabilities, technical and managerial support strongly correlate with AI adoption. Managerial capability indirectly influences AI adoption through its impact on managerial support and AI innovation attributes, highlighting the pivotal role of managerial competence in fostering adoption.

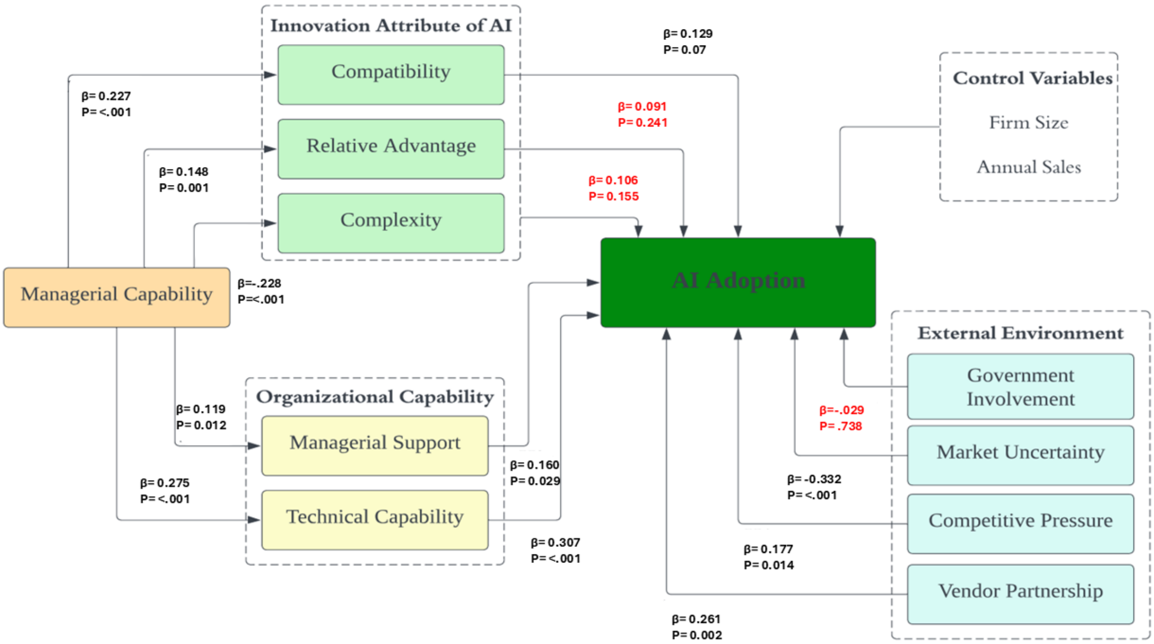

Figure 8. An Overview of the Research Model Findings

Source: Author's Creation

In the external environment, government involvement shows a weak negative relationship with AI adoption, suggesting the need for supportive policies balanced with regulatory considerations. Competitive pressure positively influences AI adoption, emphasizing the strategic imperative of adopting new technologies amid intense competition. Market uncertainty negatively affects AI adoption, reflecting challenges in decision-making and strategizing amidst market unpredictability. Vendor partnership positively correlates with AI adoption, highlighting the significance of collaborating with vendors to facilitate adoption and enhance competitiveness.

The findings validate the proposed model's efficacy in identifying key factors contributing to successful AI adoption. These factors encompass organizational capabilities, AI innovation attributes, and the external environment, with managerial capability playing an indirect yet influential role. The study underscores the relevance of the TOE framework in analysing AI adoption success factors, offering valuable insights for practitioners, policymakers, and researchers in the field.

6.2 Recommendations

Telecom operators must prioritise several key strategies to enhance AI adoption within the telecommunications sector. Firstly, they should focus on enhancing compatibility between AI technologies and network infrastructure. This entails thorough assessments of technological capabilities and infrastructure readiness to streamline the integration process effectively. Additionally, fostering managerial support is crucial, with top management within telecom firms needing to actively promote AI adoption by championing its strategic importance, allocating resources effectively, and providing clear guidance and support throughout the adoption procedure.

Furthermore, organizations should invest in enhancing technical capabilities to facilitate the seamless integration of AI technologies. This may involve upskilling IT teams, investing in infrastructure upgrades, and leveraging external expertise. In response to competitive pressures, telecom operators must effectively leverage AI technologies to innovate products and services, enhance customer experiences, and differentiate themselves in the market.

Moreover, addressing market uncertainty is paramount. Organizations should develop robust strategies for navigating uncertainties related to AI adoption, including scenario planning, risk mitigation strategies, and proactive monitoring of market trends and regulatory developments. Establishing effective vendor partnerships is also critical. Collaborating with AI vendors and partners can expedite adoption and provide access to specialized expertise and resources. Telecom firms should prioritize building strong vendor relationships based on trust, communication, and mutual benefit.

Continued research and evaluation are essential for organizations to monitor and evaluate the effectiveness of AI adoption strategies over time. This may involve conducting regular assessments, gathering stakeholder feedback, and adjusting strategies accordingly. Lastly, knowledge-sharing and collaboration initiatives within the industry are vital. Telecom operators should actively engage in such initiatives to learn from best practices, share experiences, and collectively address common challenges associated with AI adoption.

6.3 Research Limitations

The current study, like previous ones, had multiple limitations that need to be acknowledged. These limitations recognize the constraints and potential shortcomings of the dissertation, providing context for interpreting the outcomes and suggesting avenues for future research.

The first aspect to consider is the scope of this dissertation is limited to examining the factors influencing AI adoption in firms within Hungary, which restricts the generalizability of the findings to other regions with different technological landscapes, socio-economic conditions, or regulatory environments. Factors influencing AI adoption may vary significantly across countries, cultures, industries, and regulatory frameworks, further limiting the external validity of the results. To address these limitations, future research should expand the scope by adopting a multi-country or cross-cultural study design, collecting data from firms across diverse regions, cultures, and industries. Such an approach would allow for comparative analyses to identify commonalities and differences in AI adoption factors, enhancing the broader applicability and understanding of these influences in various contexts.

The second aspect is the data collection process is based on a cross-sectional survey design, capturing a snapshot of AI adoption factors at a particular time. Consequently, the research may not fully capture the dynamic nature of AI adoption processes and the evolving organizational contexts over time. To better understand the causal inferences between the research variables, it is recommended that future research employ a longitudinal study design to assess the strength and consistency of the relationships under investigation over time.

The third aspect to consider is that the research relies on self-reported data provided by respondents through surveys. This may introduce biases such as social desirability or response bias, where participants may provide answers, they perceive as favourable rather than reflecting their actual practices or experiences. Thus, future research may use a neutral survey design, employ multiple data sources, incentivize honest responses, incorporate validity checks, utilize a mixed-methods approach, and transparently disclose limitations.

Finally, the COVID-19 pandemic presented significant challenges during the research process. Restrictions on in-person interactions limited access to the data collection sites, resulting in a reduced sample size and a shift from in-person interviews to online surveys. However, efforts were made to mitigate these challenges by using digital tools and expanding the survey reach online, ensuring the validity of the findings despite the constraints. Thus, in future research, it is recommended that researchers incorporate flexible methodologies, leverage digital tools for remote data collection, and diversify data sources to mitigate disruptions. Establishing strong communication channels and adapting ethical protocols for virtual settings can enhance participant engagement and data quality.

7. NOVEL FINDING

The primary aim of the dissertation was to empirically investigate the impact of AI adoption factors on AI adoption in telecommunications firms in Hungary. By creating a research model and analytical tools based on the TOE and DOI theories, Similar to prior research on IT adoption, this study's results offer tangible proof of companies' perspectives regarding integrating AI applications. The study results indicate that many factors positively impact the potential adoption of AI applications to support firms' efficiency, competitiveness, and performance.

The findings of this dissertation contribute novel insights into the dynamics of AI adoption within firms. Through rigorous empirical testing, existing theoretical frameworks such as the TOE and DOI theories are validated and refined, enhancing our understanding of the factors influencing technology adoption. Furthermore, unique contextual factors that shape the adoption process are uncovered by examining AI adoption in diverse organizational settings, including Hungarian firms. These insights underscore the importance of considering the local context and external environment when implementing new technologies and provide valuable lessons for firms operating in different cultural environments.

The research offers practical recommendations and guidelines for firms adopting AI technologies regarding managerial implications. Grounded in empirical evidence, these recommendations address the complexities of the adoption process and empower managers to make informed decisions. Additionally, the study identifies challenges or barriers to AI adoption, highlighting areas where firms may need to effectively focus their efforts to overcome adoption hurdles.

Furthermore, as part of the research methodology, a Hungarian-translated version of the research survey was developed to guarantee the inclusivity and comprehensibility of the study's outcomes within the Hungarian organizational context. This initiative facilitated data collection from Hungarian firms and highlighted the importance of linguistic and cultural considerations in research design. By providing a localized survey instrument, the study acknowledges the significance of language accessibility in engaging diverse stakeholders and obtaining representative data. This approach contributes to the methodological rigor of the research and underscores the commitment to capturing nuanced insights into AI adoption dynamics across different cultural and linguistic settings.

Moreover, examining government involvement and regulatory frameworks reveals novel insights into how external factors shape AI adoption within organizations. These findings present valuable guidance for policymakers and industry leaders seeking to create an enabling environment for technology adoption and innovation. By exploring the perceptions and experiences of employees involved in AI adoption processes, the dissertation sheds light on the multifaceted nature of AI adoption dynamics.

Lastly, the dissertation identifies gaps in the existing literature and suggests avenues for future research to advance our understanding of AI adoption dynamics. By highlighting areas where further investigation is needed, the study guides scholars toward new research questions and methodologies that can contribute to ongoing discourse. These novel findings deepen our understanding of AI adoption and provide valuable insights for academia and business.

SUMMARY

This study has addressed the phenomenon of AI diffusion in organizational settings, focusing on evaluating its top management functions in enhancing AI adoption and facilitating the adoption of AI with human intelligence. It also aims to enhance comprehension of the most impactful factors influencing AI adoption in businesses. The overarching objective is to offer insights for academia, potential AI adopters, governmental bodies, AI suppliers for organizations, policymakers, and research about AI adoption. These insights are valuable for preparing leaders and organizations for technological shifts associated with the growing dependence on AI, connectivity, machine learning, and other recent technological innovations.

Additionally, various reasons have motivated my selection of this research domain, including my curiosity about forecasting and comprehending the trajectory of management science in an era heavily influenced by AI. I also recognize the importance of predicting and comprehending the trajectory of management science in an era increasingly dominated by AI. The recent surge in AI adoption across industries underscores the urgent need for a thorough understanding of the implications and applications. Moreover, after the COVID-19 pandemic, which has reshaped markets and accelerated digital transformation, organizations are more inclined to integrate AI technologies into their operations. This convergence of factors has fueled my passion to delve into the dynamics of AI adoption in firms, exploring its impact on management practices, organizational performance, and the broader socio-economic landscape.

The dissertation comprises seven chapters, encompassing the study's analytical and theoretical elements and presenting results and conclusions. Initially, the introduction delves into the study phenomenon, offering a brief overview of the research topic, identifying the research problem, and defining the gaps the research seeks to address. Chapter One summarizes these research gaps into a precise aim, objectives, and research questions, serving as the foundation to guide the subsequent phases of the study and aiding in the evaluation of study findings. Additionally, it offers a brief overview of the research hypotheses.

The second chapter provides a comprehensive review of previous literature related to the research topic, encompassing the definition and evolution of AI, modern AI technologies and their applications, and key fields within AI such as machine vision, expert systems, etc. The chapter also discusses various AI applications, including common ones like customer service chatbots and speech and voice services for customers, while addressing the benefits and potential risks associated with AI. Furthermore, it delves into the theoretical framework for AI

adoption, exploring literature on IT adoption, theories and models, and the theoretical framework for artificial intelligence adoption.

Chapter three presents the structure of the research model and hypotheses. The framework visually depicts the study constructs and the anticipated relationships among the research variables. Furthermore, it defines the research variables, explores their representation in previous literature, and investigates their predictive capacity in elucidating the phenomenon of IT innovation adoption. The investigated factors were categorized into the following constructs: first, the innovation attributes of AI, including complexity, compatibility, and relative advantage; second, the TOE theory presented with organizational capability, including managerial support and technical capability, and the external environment, including government involvement, market uncertainty, competitive pressure, and vendor partnership; and third, managerial capability. Finally, the research hypotheses were thoroughly presented and elucidated following the introduced research model.

Chapter four comprehensively describes of the research methodology used to address the study questions. Additionally, it introduces the research design, approach, data collection methods, sampling strategy, research population, data sources, data analysis procedures and techniques, and research instruments. Furthermore, it explains the parameters that ensure research quality and the ethical considerations incorporated into the research design. The research was conducted with top leaders in Hungarian telecommunications companies. Data were collected through an online questionnaire, and personally administered questionnaires were conducted to obtain the necessary responses. A total of 191 valid responses were received and further analyzed.

Chapter five discusses the outcomes derived from the quantitative analysis of research data. It includes testing the research hypotheses and presenting findings and conclusions regarding the relationships among the research variables outlined in the research model. The analysis encompasses data alteration, transformation, and assessment using SPSS 25 software to generate meaningful insights that address the study questions. Initially, descriptive statistics were employed to enhance comprehension of the demographic characteristics within the sample. Additionally, tests for normality of distribution were employed to ensure that the sample data followed a normal distribution pattern.

Further analyses were undertaken to evaluate the validity and reliability of the research instrument. Consequently, factor analysis was executed to explore the fundamental structure of the items related to research variables, and the alpha value was calculated to gauge its reliability.

Subsequently, upon confirmation of validity and reliability, the research hypotheses underwent testing using multiple regression analysis, and the findings were subsequently presented.

Chapter Six presented the research and analyzed the findings to conclude, addressing the research objectives and responding to the research question. It underscores their importance and contributions to the research domain. The study considers the implications of the research for theory, practice, and policy. Moreover, the chapter provides suggestions to researchers, organizations, policymakers, and leaders concerning interpreting these findings and suggests additional areas of interest while acknowledging the research limitations.

Chapter 7, the final chapter, emphasizes the dissertation's importance and original novel results.

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List of publications related to the dissertation

Articles, studies (4)

1. **Odeibat, A. S. A.**: The impacts of artificial intelligence on the future of marketing and customer behaviour.
   Cross-Cultural Management Journal. 26 (1), 19-34, 2024. ISSN: 2286-0452.
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   Journal of Agricultural Informatics. 12 (1), 52-59, 2021. EISSN: 2061-862X.
   DOI: http://dx.doi.org/10.17700/jai.2021.12.1.597

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5. **Odeibat, A. S. A.**, Mohammad, R., Abu-Zreig, M.: Integrated environmental management and GPS-X modelling for current and future sustainable wastewater treatment: A case study from the Middle East.
   Heliyon. 10 (14), 1-20, 2024. ISSN: 2405-8440.
   DOI: http://dx.doi.org/10.1016/j.heliyon.2024.e34164
   IF: 3.4 (2023)

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The Candidate's publication data submitted to the iDEa Tudóstér have been validated by DEENK on the basis of the Journal Citation Report (Impact Factor) database.

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APPENDICIES

Appendix (1) Questionnaire

Dear Sir/Madam,

I hope this email finds you well. I am writing to invite your esteemed company to participate in a survey on the adoption of Artificial Intelligence (AI) technologies or applications in firms. Your valuable insights will greatly contribute to our research in this field and help us better understand the challenges and opportunities associated with AI adoption. The primary objective of this survey is to explore the factors that influence the adoption of AI technologies and gather information from companies that currently offer or plan to adopt AI technologies. By participating, your company will play a vital role in shaping the future of AI adoption, as the findings will not only contribute to the field of AI research but also assist companies in making informed decisions regarding AI implementation. The survey is targeted towards top management and expert related to this field within your organization. It comprises a series of questions that pertain to your company's experience and expectations for AI adoption. The estimated time required to complete the survey is approximately 15 minutes. **Rest assured that all the information you provide will be treated with the utmost confidentiality and will not be disclosed to any third parties.** Your participation in this survey is entirely voluntary, and we genuinely appreciate your honest feedback. By sharing your valuable insights, you will contribute to the advancement of AI technologies and their successful integration into various industries. To participate in the survey, please find the attached document that contains the survey questionnaire. The survey is available in both English and Hungarian, allowing you to select your preferred language for completion. **Additionally, I have attached a confidentiality statement that outlines our commitment to protecting your information.** Should you have any questions, or concerns, or require further assistance, please do not hesitate to contact us. We are here to provide any clarification you may need. Thank you in advance for your time and consideration in completing this important questionnaire. Your input will make a significant impact on our research and contribute to the growth and development of AI technologies.

Best regards,

EnglishSurvey: https://docs.google.com/forms/d/1kfSEsOFueBTygbluMwxdtumDAha1s4rmNPVW1ZqaEHg/edit

Ayat Sami Odeibat

Tisztelt Hölgyem/Uram!

Remélem hogy ez az e-mail jó egészségben találja.

Annak érdekében írom levelem hogy meghívjam tisztelt vállalatát egy felmérési részvételre a Mesterséges Intelligencia (MI) technológiák és alkalmazások vállalkozásokban történő bevezetéséről. Értékes meglátásai nagyban hozzájárulnak az ezen területen végzett kutatásainkhoz, és segítenek jobban megérteni az MI alkalmazásaival kapcsolatos kihívásokat és lehetőségeket. A felmérés elsődleges célja, hogy feltárja azokat a tényezőket, amelyek befolyásolják az MI technológiák alkalmazását, és információkat gyűjtsön azoktól a vállalatoktól, amelyek jelenleg MI technológiákat használnak vagy terveznek bevezetni. Részvétele révén a vállalata fontos szerepet játszik az MI bevezetésének jövője kialakításában, mivel az eredmények nemcsak az MI kutatás területéhez járulnak hozzá, hanem segítik a vállalatokat az MI technologiák megvalósításával kapcsolatos körültekintett döntések meghozatalaiban is. A felmérésben a felsővezetőség, és a releváns területen jártas szakemberek meglátása és visszajelzése iránymutató számunkra. A felmérésben található kérdéssor a vállalat MI-val kapcsolatos tapasztalataira és az MI alkalmazásával kapcsolatos elvárásokra vonatkoznak. A felmérés kitöltése körülbelül 15 percet vesz igénybe. **Biztosítjuk, hogy az Ön által közölt információkat a lehető legbizalmasabban kezeljük, a nyilatkozott adatokat tiktoktartás köti, és harmadik félnek nem adjuk tovább.** A felmérésben nincsenek helytelen válaszok, csupán a tapasztalataira, meglátásaira vagyunk kiváncsiak. Értékes válaszaival hozzájárul az MI technológiák fejlődéséhez és sikeres integrációjához a különböző szektorokban. A felmérésben való részvételhez, kérjük, tekintse meg a mellékelt dokumentumot, amely tartalmazza magát a kérdőívet. A kérdőív angol és magyar nyelven is elérhető, így kiválaszthatja a számára megfelelő nyelvet. **Továbbá, csatoltam egy titoktartási nyilatkozatot, amely átfogóan leírja az Ön adatainak védelme iránti elkötelezettségünket.**

Bármilyen kérdése támadna a kérdőívvel kapcsolatban, szívesen várjuk Kedves megkeresését kételyek eloszlatása érdekében. Előre is köszönöm a kérdőív kitöltésére szánt idejét, Az Ön visszajelzése jelentős hatással lesz kutatásainkra.

Magyarfelmérés: https://docs.google.com/forms/d/1b_tWa8Ph6V1um7h6H970_pIp1tz7PwQZpLSM8s6Op6A/edit?pli=1

Tisztelettel:
Ayat Sami Odeibat

Appendix (1A) Questionnaire Questions

The Influence of The Expected Factors For Adopting Artificial Intelligence Applications In Firms' Management. Research Survey

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Please indicate your response to the following items on a scale of 1 to 7, where 1= Strongly Disagree, 4=Neutral, and 7=Strongly Agree. There are no right or wrong answers, so please only state your opinion.

1) Strongly disagree 2) Disagree 3) Somewhat disagree 4) Neutral 5) Somewhat agree 6) Agree 7) Strongly agree

Government involvement	SD	D	SWD	N	SWA	A	SA
1.The specification and stability of government policies are beneficial for business operation.	1	2	3	4	5	6	7
2.The government can provide financial aid.	1	2	3	4	5	6	7
3.The government support and help are very important for us to innovate.	1	2	3	4	5	6	7
Market factor /uncertainty	SD	D	SWD	N	SWA	A	SA
4. There is a trend in our principal industry to utilize more AI technologies for business	1	2	3	4	5	6	7
development and applications.	1	2	3	4	5	6	7
5. AI has broad application prospects in our principal industry.	1	2	3	4	5	6	7
6. AI can help our company to gain competitiveness.	1	2	3	4	5	6	7
Competitive pressure	SD	D	SWD	N	SWA	A	SA
7. The rate of innovation of new operating processes and new products or services in our principal industry has increased dramatically.	1	2	3	4	5	6	7
8. An industry moves to utilize the AI technologies for innovation would put pressure on our company to do the same.	1	2	3	4	5	6	7
9. There is tough price competition in our industry.	1	2	3	4	5	6	7
10. There is tough competition on product/service quality.	1	2	3	4	5	6	7
Vendor partnership	SD	D	SWD	N	SWA	A	SA
11. We have had no difficulty in obtaining assistance from our vendors/partners.	1	2	3	4	5	6	7
12. Our vendors/partners are trustworthy.	1	2	3	4	5	6	7
13. We have very close relationships with vendors/partners.	1	2	3	4	5	6	7
Managerial capability	SD	D	SWD	N	SWA	A	SA
14. We have clear goals and objectives to adopt AI technologies.	1	2	3	4	5	6	7
15. The inter-department cooperation is very important to adopt AI technologies.	1	2	3	4	5	6	7
16. The inter-department communication is very important to adopt AI technologies.	1	2	3	4	5	6	7
Managerial support	SD	D	SWD	N	SWA	A	SA
17. Our managers explicitly demonstrate to support the adoption of AI.	1	2	3	4	5	6	7
18. Our managers are willing to take risks involved in the adoption of AI.	1	2	3	4	5	6	7
19. Our managers have the ability to exploit new technologies before our competitors	1	2	3	4	5	6	7
20. Our managers have the ability to leverage IT new technologies as a strategic core competence	1	2	3	4	5	6	7
Technical capability	SD	D	SWD	N	SWA	A	SA
21. We have standardized process for IT innovation.	1	2	3	4	5	6	7

22. We have the ability to quickly integrate new AI technologies into our existing infrastructure	**1**	**2**	**3**	**4**	**5**	**6**	**7**
23. Our IT strategies supports our business strategies	**1**	**2**	**3**	**4**	**5**	**6**	**7**
Innovation attributes of AI							
Compatibility	**SD**	**D**	**SWD**	**N**	**SWA**	**A**	**SA**
24. AI application is compatible with our current communication/network environment.	**1**	**2**	**3**	**4**	**5**	**6**	**7**
25. AI application is compatible with our current software environment.	**1**	**2**	**3**	**4**	**5**	**6**	**7**
26. AI application is compatible with our current hardware environment.	**1**	**2**	**3**	**4**	**5**	**6**	**7**
27. AI application is compatible with computerized data resources	**1**	**2**	**3**	**4**	**5**	**6**	**7**
Relative advantage	**SD**	**D**	**SWD**	**N**	**SWA**	**A**	**SA**
28. AI application can increase revenues and profitability.	**1**	**2**	**3**	**4**	**5**	**6**	**7**
29. AI application can get higher employee productivity.	**1**	**2**	**3**	**4**	**5**	**6**	**7**
30. AI application can improve customer service.	**1**	**2**	**3**	**4**	**5**	**6**	**7**
31. AI application can promote flexibility and integration.	**1**	**2**	**3**	**4**	**5**	**6**	**7**
Relative risk/complexity	**SD**	**D**	**SWD**	**N**	**SWA**	**A**	**SA**
32. Adopting AI innovation lacks application maturity.	**1**	**2**	**3**	**4**	**5**	**6**	**7**
33. There has been a high cost for AI application and migration.	**1**	**2**	**3**	**4**	**5**	**6**	**7**
34. Adopting AI innovation is time consuming.	**1**	**2**	**3**	**4**	**5**	**6**	**7**
AI adoption	**SD**	**D**	**SWD**	**N**	**SWA**	**A**	**SA**
35. A timely AI technical implementation and application migration plan has been developed.	**1**	**2**	**3**	**4**	**5**	**6**	**7**
36. A financial budget and a migration schedule have been approved.	**1**	**2**	**3**	**4**	**5**	**6**	**7**
37. Our customers highly accept new products and services using AI innovations.	**1**	**2**	**3**	**4**	**5**	**6**	**7**
38. We get improvement in the competitive position after adopting AI innovation.	**1**	**2**	**3**	**4**	**5**	**6**	**7**

Background Information	
39. If you're anticipating that your company will adopt AI in the future. How do you think it will happen? At what stage of AI adoption is your organization currently engaged?	☐ Not considering ☐ More than 5 years ☐ Between 2 and 5 years ☐ between 1 and 2 years ☐ Less than 1 year ☐ Have already adopted service, infrastructure or platforms of AI.
40. Which of the following AI applications do you think your company should adopt first?	☐ Chatbot ☐ Voice Assistant ☐ Intelligent Network Management ☐ Build Artificial ☐ Intelligence Platform ☐ Others: ……
41. Current position	☐ General manager ☐ Senior manager ☐ Middle manager

	☐ line Manager ☐ Team leader ☐ Engineer ☐ Others……………
42. Number of employees	☐ Less than 500 ☐ 500-999 ☐ 1000-1400 ☐ 1500-1999 ☐ 2000-2499 ☐ Over 2500
43. Annual sales ($) for most recent year	☐ Less than 100 million 1 ☐ 100-499 million 2 ☐ 500-1 billion 3 ☐ over 1 billion 4
44. Group of companies: May you include the name of the company you are working for?	……………..
45. Age:	☐ less than 30 ☐ 31-40 ☐ 41-50 ☐ 51-60 ☐ 5)>60
46. Level of education	☐ High school ☐ Bachelor's degree ☐ master's degree ☐ Doctoral degree
47. Please indicate the country where your company is located?	…………..

A Mesterséges Intelligencia (MI) alkalmazások bevezetésének várható hatásai cégvezetésben.

Kutatási kérdőív

Kérjük, 1-től 7-ig terjedő skálán jelölje meg a következő kérdésekre adott válaszát, ahol 1 = Egyáltalán nem értek egyet, 4 = Semleges és 7 = Teljesen egyetértek. A kérdésekre nincsenek "jó" vagy "rossz" válaszok, teljes mértékben a véleményére vagyunk kiváncsiak.

1) Egyátalán nem értek egyet (EN) 2) Nem értek egyet (NEE) 3) Némileg nem értek egyet (NNE) 4) Semleges (S) 5) Némileg egytértek (NE) 6) Egyetértek (E) 7) Teljes mértékben egyetértek (TME)

Közigazgatási részvétel	**EN**	**NEE**	**NNE**	**S**	**NE**	**E**	**TME**
1. A kormányzati politikák specifikációja és stabilitása előnyös az üzleti működés szempontjából	1	2	3	4	5	6	7
2. A kormány pénzügyi segítséget tud nyújtani	1	2	3	4	5	6	7
3. Az innovációhoz nagyon fontos az állami támogatás és segítség	1	2	3	4	5	6	7
Piaci tényezők	**EN**	**NEE**	**NNE**	**S**	**NE**	**E**	**TME**
4. Fő iparágunkban megfigyelhető az a tendencia, hogy több mesterséges intelligencia technológiát használunk az üzletfejlesztéshez és az alkalmazásokhoz	1	2	3	4	5	6	7
5. Az MI széles körű alkalmazási kilátásokkal rendelkezik fő iparágunkban	1	2	3	4	5	6	7
6. A mesterséges intelligencia segíthet vállalatunk versenyképességének növelésében	1	2	3	4	5	6	7
Versenynyomás	**EN**	**NEE**	**NNE**	**S**	**NE**	**E**	**TME**
7. Fő iparágunkban drámaian megnőtt az új működési folyamatok és új termékek vagy szolgáltatások innovációjának aránya	1	2	3	4	5	6	7
8. A mesterséges intelligencia technológiák innovációs célú felhasználására irányuló iparági lépések nyomást gyakorolnának vállalatunkra, hogy az ugyanezt tegye	1	2	3	4	5	6	7
9. Az árak terén igen erős a verseny az iparágunkban	1	2	3	4	5	6	7
10. A termék/szolgáltatás minősége terén erős verseny folyik	1	2	3	4	5	6	7
Kereskedői partnerség	**EN**	**NEE**	**NNE**	**S**	**NE**	**E**	**TME**
11. Nem okoz nehézséget a partnereinktől segítséget kérni	1	2	3	4	5	6	7
12. Partnereink megbízhatóak	1	2	3	4	5	6	7
13. Szoros kapcsolatban állunk partnereinkkel	1	2	3	4	5	6	7
Vezetői képesség	**EN**	**NEE**	**NNE**	**S**	**NE**	**E**	**TME**
14. Világos célkitűzéseink vannak az MI-technológiák bevezetésére	1	2	3	4	5	6	7
15. A részlegek közötti együttműködés nagyon fontos az MI-technológiák alkalmazásához	1	2	3	4	5	6	7
16. A részlegek közötti kommunikáció nagyon fontos az MI-technológiák alkalmazásához	1	2	3	4	5	6	7
Vezetői támogatás	**EN**	**NEE**	**NNE**	**S**	**NE**	**E**	**TME**
17. Vezetőink kifejezetten támogatják az MI bevezetését	1	2	3	4	5	6	7
18. Vezetőink készek releváns kockázatokat vállalni az MI bevezetésével kapcsolatban	1	2	3	4	5	6	7
19. Vezetőink képesek kiaknázni az új technológiákat versenytársaink előtt	1	2	3	4	5	6	7
20. Vezetőink jól ismerik hogyan használható az MI technológia az üzleti teljesítmény növelésére	1	2	3	4	5	6	7
Műszaki adottság	**EN**	**NEE**	**NNE**	**S**	**NE**	**E**	**TME**

21. Az informatikai innovációhoz szabványosított eljárással rendelkezünk	**1**	**2**	**3**	**4**	**5**	**6**	**7**
22. Lehetőségünk van az új MI-technológiák gyors integrálására meglévő infrastruktúránkba	**1**	**2**	**3**	**4**	**5**	**6**	**7**
23. Az informatikai stratégiáink támogatják üzleti stratégiáinkat	**1**	**2**	**3**	**4**	**5**	**6**	**7**
Kompatibilitás	**EN**	**NEE**	**NNE**	**S**	**NE**	**E**	**TME**
24. Az MI alkalmazás kompatibilis a jelenlegi kommunikációs/hálózati környezetünkkel	**1**	**2**	**3**	**4**	**5**	**6**	**7**
25. Az MI alkalmazás kompatibilis a jelenlegi szoftverkörnyezetünkkel	**1**	**2**	**3**	**4**	**5**	**6**	**7**
26. Az MI alkalmazás kompatibilis a jelenlegi hardverkörnyezetünkkel	**1**	**2**	**3**	**4**	**5**	**6**	**7**
27. Az MI alkalmazás kompatibilis a számítógépes adatforrásokkal	**1**	**2**	**3**	**4**	**5**	**6**	**7**
Relatív előny	**EN**	**NEE**	**NNE**	**S**	**NE**	**E**	**TME**
28. Az MI alkalmazás növelheti a bevételeinket és jövedelmezőségünket	**1**	**2**	**3**	**4**	**5**	**6**	**7**
29. Az MI alkalmazás növelheti az alkalmazottak termelékenységét	**1**	**2**	**3**	**4**	**5**	**6**	**7**
30. Az MI alkalmazás javíthatja az ügyfélszolgálatunkat	**1**	**2**	**3**	**4**	**5**	**6**	**7**
31. Az MI-alkalmazások elősegíthetik a rugalmasságot és integrációt	**1**	**2**	**3**	**4**	**5**	**6**	**7**
Relatív kockázat/komplexitás	**EN**	**NEE**	**NNE**	**S**	**NE**	**E**	**TME**
32. Az MI innováció kihasználása még nem érte el az alkalmazási érettséget	**1**	**2**	**3**	**4**	**5**	**6**	**7**
33. Az MI alkalmazása magas költségekkel jár	**1**	**2**	**3**	**4**	**5**	**6**	**7**
34. Az MI innovációk megvalósítása időigényes	**1**	**2**	**3**	**4**	**5**	**6**	**7**
Az MI használata	**EN**	**NEE**	**NNE**	**S**	**NE**	**E**	**TME**
35. Az MI technológia bevezetésére és alkalmazására elkészített tervekkel rendelkezünk	**1**	**2**	**3**	**4**	**5**	**6**	**7**
36. A vezetők elfogadták a költségvetési és bevezetési ütemtervet	**1**	**2**	**3**	**4**	**5**	**6**	**7**
37. Ügyfeleink elégedettek az MI innovációit alkalmazó új termékekkel és szolgáltatásokkal	**1**	**2**	**3**	**4**	**5**	**6**	**7**
38. Az MI innováció bevezetése után javulást érhetünk el a versenyhelyzetünkben	**1**	**2**	**3**	**4**	**5**	**6**	**7**

Háttér-információ	
39. Ha arra számít, hogy cége a jövőben bevezeti a Mesterséges Intelligenciát, mit gondol, hogyan fog ez történni? Az MI alkalmazásának melyik szakaszában van jelenleg vállalata?	☐ Nincs tervben ☐ Több mint 5 éven belül van tervben ☐ 2 és 5 éven belül van tervben ☐ 1 és 2 éven belül van tervben ☐ Kevesebb mint 1 éven belül van tervben ☐ Már rendelkezünk alkalmazott Mesterséges Intelligenciával
40. Ön szerint az alábbi Mesterséges Intelligencia-alkalmazások közül melyiket kellene először alkalmaznia vállalatának?	☐ Chatbot ☐ Hangassisztens ☐ Intelligens hálózatkezelés ☐ Mesterséges Intelligencia-platform kiépítése

	☐ Más: ……
41. Jelenlegi pozíciója	☐ Ügyvezető igazgató ☐ Vezető menedzser ☐ Középvezető ☐ Osztályvezető ☐ Csoportvezető ☐ Mérnök ☐ Más……………
42. Az ön vállalata alkalmazottjainak száma	☐ Kevesebb mint 500 ☐ 500-999 ☐ 1000-1400 ☐ 1500-1999 ☐ 2000-2499 ☐ Több mint 2500
43. Éves értékesítése dollárban, a legutóbbi pénzügyi évre vonatkozóan	☐ Kevesebb mint 100 millió ☐ 100-499 millió ☐ 500 millió -1 milliárd ☐ Több mint 1 milliárd
44. Volna kedves megosztani a cég nevét ahol tevékenykedik?	……………..
45. Az Ön kora:	☐ Kevesebb mint 30 ☐ 31-40 ☐ 41-50 ☐ 51-60 ☐ >60
46. Legmagasabb iskolai végzettsége	☐ Gimnázium, Szakközépiskola ☐ Főiskolai végzettség (BSc) ☐ Mesterképzés (MSc) ☐ Doktori végzettség (PhD)
47. Az Ön cége melyik országban található?	…………..

Appendix (1B) Confidentiality Statement

DEBRECENI EGYETEM

DEBRECENI EGYETEM
Gazdaságtudományi Kar
Ihrig Károly Gazdálkodás- és Szervezéstudományok Doktori Iskola
H-4002 Debrecen, Egyetem tér 1, Pf.: 400
Tel.: 52/508-482, e-mail: rakos.monika@econ.unideb.hu

Titoktartási nyilatkozat

Szeretnénk biztosítani, hogy a kutatási projektünkben való részvételét a lehető legnagyobb gondossággal és bizalmasan kezeljük.

Tájékoztatjuk, hogy a kérdőív segítségével gyűjtöt adatokat és információkat kizárólag tudományos és kutatási célra használjuk fel. A Debreceni Egyetem elkötelezet a vizsgálatban résztvevők bizalmas és magánéletének megőrzése mellet, és minden szükséges lépést megteszünk annak érdekében, hogy az Ön adatait megvédjük a jogosulatlan hozzáféréstől, felhasználástól vagy nyilvánosságra hozataltól.

Biztosítjuk Önt arról, hogy a kutatási projekt eredményeit kizárólag tudományos és kutatási célokra használjuk fel, és nem osztjuk meg harmadik féllel kereskedelmi vagy egyéb célokra.

Ha bármilyen aggálya vagy kérdése van a kutatási projektel kapcsolatban, kérjük, forduljon hozzánk bizalommal.

Köszönjük, hogy részvételével hozzájárul a kutatásunk eredményességéhez.

Debrecen, 2023. április 22.

Prof. Dr. Balogh Péter
Ihrig Károly Gazdálkodás- és Szervezéstudományok Doktori Iskola vezetője

DEBRECENI EGYETEM

DEBRECENI EGYETEM
Gazdaságtudományi Kar
Ihrig Károly Gazdálkodás- és Szervezéstudományok Doktori Iskola
H-4002 Debrecen, Egyetem tér 1, Pf.: 400
Tel.: 52/508-482, e-mail: rakos.monika@econ.unideb.hu

Confidentiality Statement

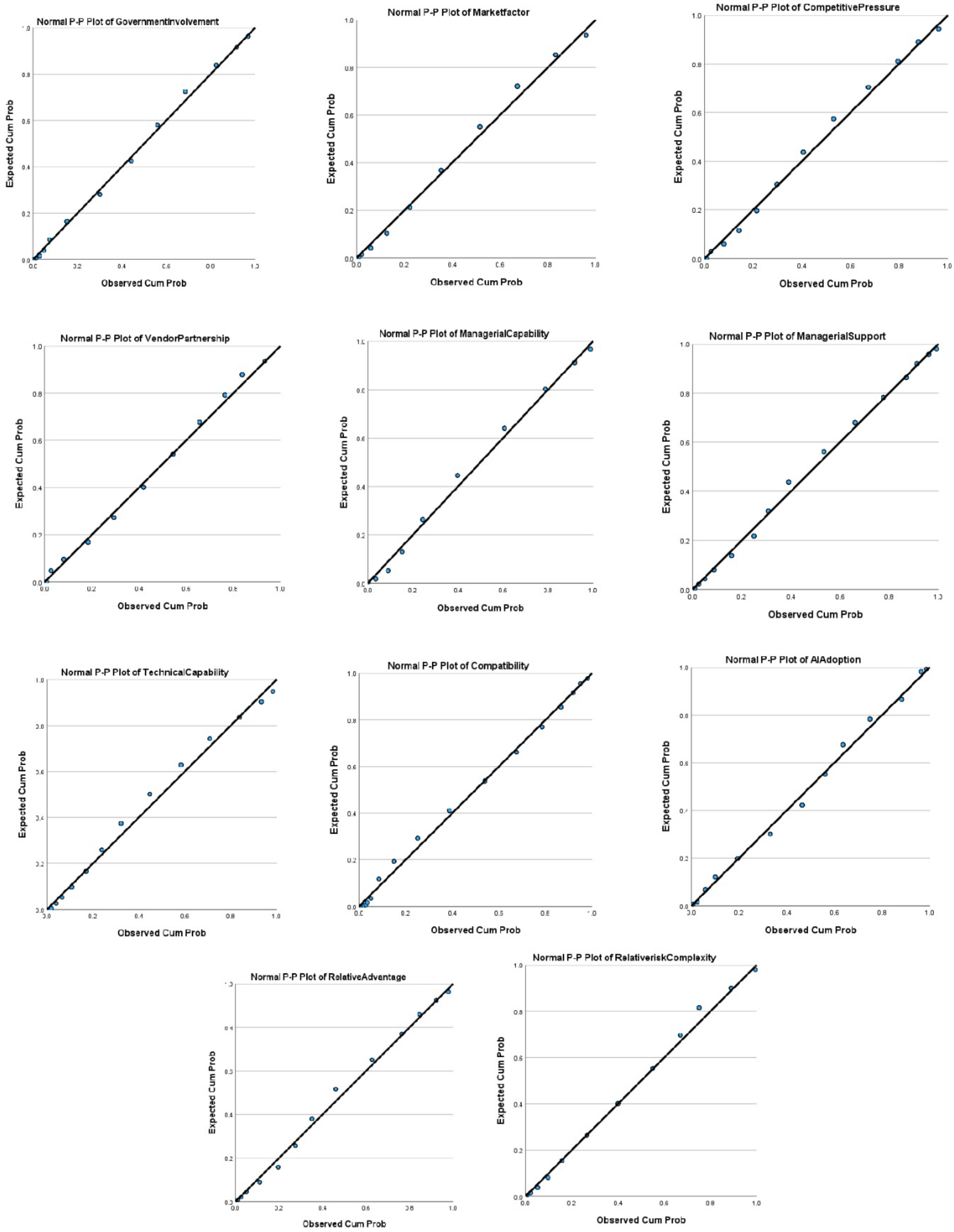
To whom it may concern,

We would like to ensure that your participation in our research project will be handled with the utmost care and confidentiality.
Please be advised that all data and information collected through this questionnaire will be used solely for academic and research purposes. The University of Debrecen is committed to maintaining the confidentiality and privacy of all participants in this study, and we will take all necessary steps to protect your data from unauthorized access, use, or disclosure.
We assure you that the results of this research project will be used only for academic and research purposes and will not be shared with any third party for commercial or other purposes.
If you have any concerns or questions about this research project, please do not hesitate to contact us. Thank you for considering our request to participate in this study, and we look forward to hearing from you soon.

Debrecen, 22.04.2023.

Prof. Dr. Balogh Péter
Head of Ihrig Károly Gazdálkozás- és Szervezéstudományok Doktori Iskola

Appendix (2) P-P plots for the Study Variables



Source: Author's Construction

Appendix (3) Total Variance Explained

Component	Initial Eigenvalues			Extraction Sums of Squared Loadings			Rotation Sums of Squared Loading[a]
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %	Total
1	9.204	24.220	24.220	9.204	24.220	24.220	5.132
2	3.146	8.278	32.498	3.146	8.278	32.498	4.733
3	2.241	5.898	38.397	2.241	5.898	38.397	4.548
4	2.111	5.556	43.953	2.111	5.556	43.953	5.015
5	1.699	4.471	48.424	1.699	4.471	48.424	5.768
6	1.451	3.819	52.243	1.451	3.819	52.243	4.065
7	1.397	3.678	55.921	1.397	3.678	55.921	3.423
8	1.265	3.328	59.249	1.265	3.328	59.249	2.869
9	1.227	3.229	62.477	1.227	3.229	62.477	3.943
10	1.184	3.116	65.593	1.184	3.116	65.593	3.097
11	1.082	2.848	68.442	1.082	2.848	68.442	1.586
12	.918	2.415	70.856				
13	.857	2.254	73.110				
14	.836	2.199	75.309				
15	.802	2.112	77.421				
16	.744	1.957	79.378				
17	.692	1.820	81.198				
18	.671	1.766	82.964				
19	.604	1.590	84.554				
20	.591	1.554	86.108				
21	.527	1.388	87.496				
22	.505	1.329	88.824				
23	.493	1.298	90.122				
24	.436	1.148	91.270				
25	.400	1.053	92.323				
26	.370	.973	93.297				
27	.351	.923	94.220				
28	.333	.876	95.095				
29	.311	.818	95.913				
30	.240	.632	96.545				
31	.232	.609	97.155				
32	.211	.555	97.709				
33	.202	.532	98.241				
34	.172	.452	98.693				
35	.170	.447	99.140				
36	.122	.322	99.462				
37	.105	.276	99.739				
38	.099	.261	100.000				

Source: Author's calculations

Appendix (4) Factors Pattern Matrix[a]

Items	Component										
	1	2	3	4	5	6	7	8	9	10	11
GI1								.391			
GI2									.635		
GI3								.794			
MF1									.602		
MF2									.855		
MF3			.537								
CP1								.539			
CP2								.448			
CP3							.826				
CP4							.881				
VP1				.632							
VP2										.571	
VP3										.507	
MC1				.459							
MC2										.801	
MC3											.603
MS1		.822									
MS2		.611									
MS3				.370							
MS4						.351					
TC1		.445									
TC2		.441									
TC3		.600									
C1	.327										
C2					.910						
C3					.813						
C4					.763						
RA1			.520								
RA2			.805								
RA3			.840								
RA4	.664										
RC1											-.763
RC2						-.909					
RC3						-.970					
AI1				.847							
AI2				.651							
AI3	.854										
AI4	.925										

Extraction Method: Principal Component Analysis. Rotation Method: Promax with Kaiser Normalization.

Source: Author's calculations