INVESTIGATION OF THE CRITICAL FACTORS

IMPACTING ORGANIZATIONAL ADOPTION OF AI TECHNOLOGY

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DECLARATION OF ORIGINALITY

I, Dilek Çabuk, certify that

- I am the sole author of this thesis and that I have fully acknowledged and documented in my thesis all sources of ideas and words, including digital resources, which have been produced or published by another person or institution;
- this thesis contains no material that has been submitted or accepted for a degree or diploma in any other educational institution;
- this is a true copy of the thesis approved by my advisor and thesis committee at Boğaziçi University, including final revisions required by them.

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ABSTRACT

Investigation of the Critical Factors

Impacting Organizational Adoption of AI Technology

Artificial Intelligence (AI) is an emerging field that continues to develop at a rapid pace. It consists of challenges and unexplored opportunities that require in-depth research. While AI technologies and applications have garnered attention in research, the adoption and integration of AI technologies remains largely unexplored. Despite all the progress, the real impact of critical factors on AI integration is still not fully understood, pointing to a critical gap in the literature that calls for further exploration. The main purpose of this study is to examine the organizational adaptation of AI technologies and identify the factors affecting it. To do this, Diffusion of Innovation Theory and the Technology, Organization, and Environment (TOE) Framework are applied in the research design. Using these two theories together ensures a basis for exploring adaptation process from an organizational side. Based on a comprehensive literature review, a theoretical model examined the effects of three major factors—technological, organizational, and environmental—on the adoption and application of AI. As a result of this research, positive and statistically significant relationship has been found between AI Adoption and Compatibility, Technical Capability, Managerial Support, Competition’s Pressure, Vendor Partnership. The research result offers important managerial support for companies to implement AI technologies. The findings serve as a basis for further research and can be utilized by IT and AI supervisors during the implementation of Artificial Intelligence technology solutions that enhance their organization's productivity and performance.

ÖZET

Yapay Zekâ Teknolojisinin Kurumsal Olarak Benimsenmesinde

Etkili Olan Kritik Faktörlerin Araştırılması

Yapay Zekâ hızla gelişmeye devam eden yeni bir alandır. Derinlemesine araştırma gerektiren karmaşık zorluklar ve keşfedilmemiş fırsatlar içermektedir. Yapay Zekâ teknolojileri ve uygulamaları araştırmada ilgi toplamış olsa da Yapay Zekâ teknolojilerinin benimsenmesi ve entegrasyonu büyük ölçüde keşfedilmemiş durumdadır. Tüm ilerlemelere rağmen, kritik faktörlerin Yapay Zekâ entegrasyonu üzerindeki gerçek etkisi hala tam olarak anlaşılmamıştır ve bu durum literatürde daha fazla araştırma gerektiren kritik bir boşluğa işaret etmektedir. Bu çalışmanın temel amacı, Yapay Zekâ teknolojilerinin örgütsel adaptasyonunu incelemek ve bunu etkileyen faktörleri belirlemektir. Bunu yapmak için, araştırma tasarımında Yeniliğin Yayılması Teorisi ve Teknoloji, Organizasyon ve Çevre (TOE) Çerçevesi uygulanmaktadır. Bu iki teorinin birlikte kullanılması, adaptasyon sürecini örgütsel açıdan keşfetmek için bir temel sağlar. Kapsamlı bir literatür incelemesine dayalı olarak, teorik bir model, Yapay Zekânın benimsenmesi ve uygulanması üzerinde üç ana faktörün (teknolojik, örgütsel ve çevresel) etkilerini incelemiştir. Bu araştırmanın sonucunda, Yapay Zekâ Benimsenmesi ve Uyumluluk, Teknik Yetenek, Yönetimsel Destek, Rekabet Baskısı, Tedarikçi Ortaklıkları arasında pozitif ve istatistiksel olarak anlamlı ilişki bulunmuştur. Araştırma sonucu, şirketlere Yapay Zekâ teknolojilerini uygulamaları için önemli yönetimsel destekler sunmaktadır. Bulgular, daha fazla araştırma için bir temel teşkil etmekte olup, BT ve Yapay Zekâ yöneticileri tarafından kuruluşlarının üretkenliğini ve performansını artıran Yapay Zekâ teknolojisi çözümlerinin uygulanması sırasında kullanılabilir.

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CHAPTER 1

INTRODUCTION

The Artificial Intelligence or AI is generally accepted as a technology that allows computers and other devices to simulate human intelligence and problem-solving abilities (Joier, 2018). AI is capable of carrying out tasks that would normally require human intelligence or assistance, either on its own or in conjunction with other technologies. Important developments have been made in AI and computer science in recent years (Andreotta, Kirkham, & Rizzi, 2022; Putha, 2022; Singh, Kumar, & Mehra, 2023). Thanks to these developments, AI has been utilized in a variety of applications used in daily life, like generative AI tools such as Open AI's Chat GPT (Henseler & van Beek, 2023), digital assistants (Brill, Munoz, & Miller, 2022), driverless cars (Bin Sulaiman, 2018), and Global Positioning System (GPS) assistance (El Sabbagh, Maher, Abozied & Kamel, 2023).

Artificial Intelligence has quickly grown to be a ubiquitous technology that touches nearly every aspect of everyday life and industrial operations (Kulkarni, Joseph, & Patil, 2024). Lada et al. (2023) points out that based on the predictions, countries, companies, and communities will be significantly impacted by the impending developments in Big Data, machine learning, and automation. Many industries have already undergone upheavals with the developments in Artificial Intelligence technology like automatization (Yang, Blount, & Amrollahi, 2024). Artificial Intelligence and other cutting-edge technologies like cloud solutions and Blockchain technologies are fundamental for every industry player in today's fiercely competitive economic world (Lada et al., 2023). In the current business environment, AI is a critical factor for companies, especially if they want to reduce costs or optimize their operations in the long run (Mijwel, 2015). AI is acknowledged as a strategic decision support and information technology innovation tool that firms can use to become more successful (Makridakis, 2017; Chen, 2019). Nortje and Grobbelaar (2020) indicate that in order to reduce costs and accelerate production, effective AI integration and deployment are required. However, despite upcoming benefits and companies' desire to implement this disruptive technology, there are some obstacles like technical obsolescence that make it difficult to adopt and apply it (Sharma, Shah, & Patel, 2022).

Artificial Intelligence inherently presents certain challenges. These challenges include high maintenance and repair costs, the risk of bugs and errors, security concerns, the requirement for extensive datasets and high-tech technical knowledge (Osipov & Ulimova, 2013). Furthermore, AI is still in the conceptualization stage, which imposes another obstacle due to its immaturity. Because of these challenges coming from its nature and immaturity of this new technology, the complexity of the adaptation process is rising. It is a complicated process that calls for the long-term provision of suitable infrastructure and resources in addition to the acquisition of software and hardware (Chen, 2019). As a result, when adopting AI into their organizational structures, businesses will encounter these challenges that are required to manage, and in order to solve them, companies wish to learn and analyze critical factors and their impacts for a smooth transition (Chen, Li, & Chen, 2021). However, in the literature, there is currently no broadly applied evaluation of AI adoption and factors effecting it available (Chen et al, 2021).

The literature extensively explores technology adoption and the factors influencing it. A range of disciplinary ideas and frameworks have been used to examine the adoption of new technologies (Gangwar, Date, & Raoot, 2014; Muafi, Gusaptono, Effendi, & Novrido, 2021; Pierri & Timmer, 2020; Reinhartz-Berger, Hartman, & Kliger, 2024). However, there is not a broad literature available in the field of Artificial Intelligence technology adoption and important factors affecting it (Chen et al, 2021; Nguyen, Nguyen, & Dang, 2022). Artificial Intelligence technology adoption is different than other new technology adoptions due to its learning and adaptive nature, which rely on high-quality data and technical complexity (Olatunde, Okwandu, Akande, & Sikhakhane, 2024). Traditional technologies are generally static tools with predefined functions; but, AI systems continuously develop and learn from data which requires ongoing updates and monitoring (Steidl, Felderer, & Ramler, 2023). Therefore, this reliance on data and technical expertise makes adopting AI more demanding for organizations.

Despite the challenges inherent in the nature of AI, a growing number of companies are inclined to adopt this technology. Therefore, it is necessary to focus in this area and make a in depth adoption factor analysis for companies to ensure their seamless transition to AI. The purpose of this study is to analyze the factors influencing AI adoption, support and guide companies, and enhance the literature by addressing these gaps.

Analyzing and finding critical factors for AI adoption at the organizational level requires the identification of the correct theories. Diffusion of Innovation, which discuss how innovations spread among individuals or organizations over time, is a theory that has been widely used in IT technologies adoption literature. However, this theory generally focuses on individual traits and from an organizational perspective. It does not offer a full view of AI adoption for companies (Chen et al,2021; Liu, 2019). Therefore, to complement this theory from an organizational perspective in detail, an additional theory was required (Amini & Bakrii 2015; Sayginer & Ercan, 2020). Based on technology adaptation literature, it is possible to apply The Technology-Organization-Environment (TOE) Framework for new technology adoption process from an organizational viewpoint.

Technology, Organization and Environment Framework explains how technical, organizational and environmental elements influence organizations' decisions for adopting technological innovations as a crucial contextual aspect (Tornatzky & Fleischer, 1990). Previous studies have successfully used this framework even though the specific components found in the three contexts may differ (Baker, 2012; Chen et al, 2021; Oliveira & Martins, 2011). It is used to look at the variables that influence the adoption of new technologies with the organizational perspective in mind (Chau & Tam, 1997; Chen et al, 2021; Kuan & Chau, 2001). Thus, the Technology-Organization-Environment (TOE) Framework (Tornatzky & Fleischer, 1990) and Diffusion of Innovation Theory (Rogers, 1983) together provide a comprehensive understanding of the elements influencing adoption of new technologies. As mentioned above, these theories have proven to be effective in organizational perspective for the adaptation of new technologies. Therefore, they serve as an important basis for understanding the adoption of Artificial Intelligence, which is also a new technology for companies. Factors that quite likely impact AI adoption within these theoretical frameworks are chosen based on the literature review on new technology adoptions.

Through careful examination of these factors on AI adoption, this study aims to address the literature gap in artificial intelligence technologies adoption. As indicated, it is possible to find wide range of new technology adoption research. Nevertheless, Artificial Intelligence is one of the most up-to-date innovation technologies. The majority of AI research has mostly concentrated on methods and techniques (Cui, Xu, Lv, & Wei, 2021; Elish & Boyd, 2018; Holzinger, Saranti, Molnar, Biecek, & Samek, 2022; Qi, Wu, Li, & Shu, 2007; Walczak, 2016; Wang, Liu, Liu, & Tao, 2021). The key elements that influence the adoption of AI, in particular, are overlooked. However, as it is indicated above, it is necessary to focus on these adoption factors due to increasing number of companies switching to AI technologies because they are in need of research to point the way. In the literature, it is not possible to find many studies that focus on which factors influence AI adoption in organizational perspective (Chen et. al, 2021; Nguyen et al., 2022). Therefore, our aim in this study is to help companies in identifying the critical factors affecting AI adoption and ensuring that their adaptation processes are based on these insights. As a result, the following research questions (RQ) are developed:

- RQ1: What are the key factors influencing the adoption of Artificial Intelligence technologies in organizations?
- RQ2: How do technological, organizational and environmental factors affect AI adoption?

By resolving these questions, this research aims to comprehend the critical factors that affect AI technologies adoption from an organizational perspective. Thus, this study will assist in filling the gap within new technology adoption regarding AI technologies. Additionally, it offers assistance in decision-making and resource allocation for businesses implementing this new challenging technological development.

CHAPTER 2

LITERATURE REVIEW

This section provides an overview of Artificial Intelligence technology, its historical development, challenges that it encounters, its advantages and the meaning as well as scope of AI adoption based on the literature review. Furthermore, the theoretical frameworks used in this research are explained.

2.1 Artificial Intelligence

2.1.1 What is AI?

The ability of computer systems to exhibit intelligence is known as Artificial Intelligence, or AI by the public. Various systems based on Artificial Intelligence technology have been made possible by the AI's rapid development (Wang, 2008). Thus, AI enhances efficiency and capabilities across various industries.

However, in the literature, it is not possible to give globally agreed definition for Artificial Intelligence. There are several definitions that would be important to mention. According to Joiner (2018), AI is the branch of computer science that focuses on building intelligent computers that are able to carry out activities that normally require human intellect. Russell et al. (2010, p.31) defines AI as the technology that "enables the machine to exhibit human intelligence, including the ability to perceive, reason, learn, and interact." Nguyen et al. (2022) defines AI as the idea of turning inanimate items into intelligent entities with human-like reasoning and numerous aspects of human intelligence, including learning, reasoning, problem-solving, voice recognition, and planning, are imitated by computer systems. AI is also defined as a machine's capacity to execute cognitive processes associated with human brains, including as perception, reasoning, learning, interacting with the environment, problem solving, decision making, and even exhibiting creativity (Rai, Constantinides, & Sarker, 2019). In the context of information systems and definition of Artificial Intelligence, it often emphasizes human intelligence and its cognitive processes (Collins, Dennehy, Conboy, & Mikalef, 2021).

Human intelligence distinguishes us from animals and machines, and generally Artificial Intelligence is evaluated as seeking to replicate certain aspects of this cognitive ability as exemplified above. It is considered as something that gives the computer the capacity to demonstrate human intelligence, such as reasoning, learning, perception, and interaction, among other skills (Russell & Norvig, 2020). In line with this, Lada et al. (2023) further argue that Artificial Intelligence (AI) systems are made to reason, learn from results, evaluate it, and solve issues like human cognition. However, to achieve this, AI technologies rely heavily on machine learning techniques, large datasets, and advanced algorithms, which are crucial for tasks such as information acquisition, performance enhancement, and situational adaptation (Xu et al., 2021). The better algorithms mean better reasoning, thus enabling AI to think more like human intelligence. However, as AI systems get better, understanding the underlying decision-making processes becomes essential for further development. This is because, in order to replicate human-like thinking, AI must rely on specific mechanisms for decision-making that mirror cognitive functions. At this stage, it is crucial to briefly explore how AI systems approach decision-making, the nature of AI and its types. Wolfe (1991) indicates that there are two types of decision-making processes used by machines: rule-based, where the rules are rigidly followed by the machine, and rule-following, where the computer follows the rules that are not explicitly given to it. While rule-following decision making is an attempt towards strong AI, rule-based decision making is more in line with weak AI. Currently, developments and products of weak AI have been used. On the other hand, Wang (1994) defines five ways to characterize AI: i) by structure, aiming to replicate the brain's neuron-like units; ii) by behavior, measuring AI’s ability to imitate human responses (e.g., the Turing Test); iii) by capability, evaluating problem-solving abilities like those of humans; iv) by function, focusing on replicating cognitive tasks such as reasoning and learning; and v) by principle, seeking to identify the fundamental cognitive principles underlying human intelligence to guide AI development.

Thus far, the definition of AI and its similarities to human intelligence have been discussed; however, it is crucial to recognize that AI is also fundamentally different from human intelligence. The concept of Artificial Intelligence is similar to that of human intelligence since it uses the human mind as the finest illustration of "intelligence." But AI differs as well since it mimics cognitive processes instead of building a fully human-like being. People generally acknowledge today's sophisticated computers as intelligent as they can learn new things and create their choices in light of the information they consume. Although we understand that skill, it's a completely distinct kind of intellect than what human beings have (De Cremer & Kasparov, 2021). This situation raises the question of what intelligence actually is. Cave (2020) researches for the evolution of the concept of intelligence and shows how the definition of intelligence has been made in various ways from classical rationality and wisdom ideas to more modern, quantitative definitions of problem-solving and adaptability throughout history. There are certain debates in the literature focusing on the definition of intelligence and its impression in AI technologies (Boden, 2016; De Cremer & Kasparov, 2021). To understand what intelligence is, experimental tests were created thanks to advancements in programming languages and computational devices in the past fifty years (Buchanan, 2005). However, besides these tests, other aspects of intelligence were also researched.

There are many definitions for AI and each of these AI definitions captures a distinct fact of human intelligence as a research target that can be attained to varying degrees (Wang, 2008). Although AI can take many forms, it is a frequent misconception to assume that there is a "true" ("real," "natural") definition of "intelligence" that it must conform to (Wang, 2008). AI cannot simply apply definitions of "intelligence" from fields like psychology, where intelligence highlights variations among human cognitive abilities, since AI is primarily concerned with the distinction between human and machine intelligence (Wang, 2008). Intelligence has a value-laden nature, societal values and cultural biases, giving priority to some knowledge and cognitive abilities over others, consequently, shapes this concept, which may also influence AI system designs (Cave, 2020). Because AI's future depends on its developers' values and assumptions, a more diverse and inclusive view of intelligence is needed.

These discussions revolving around AI and intelligence also give rise to another debate, whether AI will take the place of human skills if it would become like human intelligence. In *AI Should Augment Human Intelligence, Not Replace It,* Cremer and Kasparov (2021) discuss a cooperative strategy in which AI complements human skills rather than takes their place. The term 'Augmented Intelligence' is used to explain combining strengths of AI and human because AI's strengths in speed, accuracy, and consistency while human intuition, creativity, and cultural awareness can produce superior outcomes in lots of areas from business to complex problem-solving (De Cremer & Kasparov, 2021). All these literature display that the real understanding of both artificial intelligence and human intelligence lies in their integration. However, it is also necessary to understand real-world implications of AI, working together with human intelligence.

Exploring what artificial intelligence is, the theoretical understanding of AI and its relationship to human intelligence provide important context to comprehend the essence of Artificial Intelligence. However, it is also crucial to examine how AI theories manifest in practice. Detailing the reflection of AI in real world practices would provide deep understanding before focusing on their adoption process.

AI is a broad field encompassing various technologies and applications. Key types of AI include: Machine Learning, which uses algorithms to learn from data and make predictions in; Deep Learning, a subset of machine learning that uses neural networks for tasks such as image and speech recognition; Natural Language Processing (NLP), enabling computers to understand human language and voice recognition; Computer Vision, which allows machines to interpret images, applied in facial recognition and object detection; Robotics, enabling robots to perform tasks autonomously; Expert Systems, which make decisions based on rules, commonly used in medical and financial fields; and Neural Networks, which are used in a range of applications like image recognition and autonomous driving, allowing computers to learn from data (Al-Ansi & Al-Ansi, 2023). These Artificial Intelligence technologies have found applications in various fields focusing on different areas. For example, NLP includes AI Technologies like Speech Recognition, Machine Translation, Chatbots, AI chips comprise neuromorphic Hardware, GPU accelerators, Computer Vision contains image classification and segmentation (Amin

& Mandapuram, 2021; Ayanouz, Abdelhakim, & Benhmed, 2020; Karn et al.,2024; Pang, 2022). In 'Artificial Intelligence in Product Lifecycle Management', Wang et al. (2021) summarizes technology fields of AI, displaying its wide range of applications and capabilities. 8 main technology fields are identified by them, namely Independent AI, AI algorithms and engines, AI chips, Computer vision, Natural Language Processing, AI-driven development, Immersion technology, AI-Based Integrated Applications. For each domain, detailed application areas are specified and technologies without a main category are categorized under 'Other'. Figure 1 below displays key types of AI and technologies presented by Wang et al. (2021).

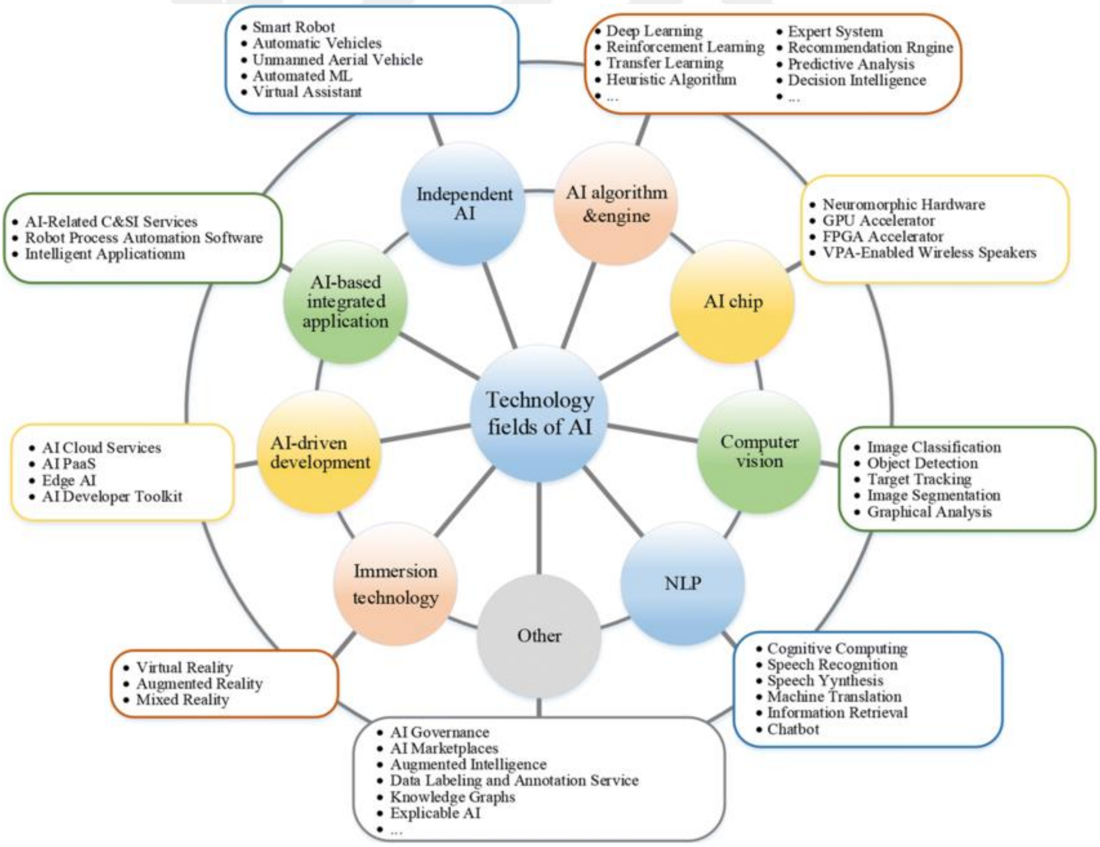

Figure 1. Artificial Intelligence technologies' fields (adapted from Wang et al., 2021, p.779)

The literature on Artificial Intelligence includes these subcategories of AI with focus points, and each field researches a distinct area. Certain studies look at AI applications in these particular fields mentioned above (Ambrogio et al., 2023; Chapelle & Chung, 2010; Holland, Hosny, Newman, Joseph & Chmielinski, 2020; Jane, 2022; Mazurek & Małagocka, 2019; Nalbant & Uyanık, 2021; Yuen & Spjut, 2024; Wu, 2021; Zhang, Feng, Zhao, & Zhang, 2024). Furthermore, some researchers examine the theoretical underpinnings of artificial intelligence (Chi-Hsien & Nagasawa, 2019; Heyder, Passlack, & Posegga, 2023; Krijger, 2022; Lindgren, 2023; Mohamed, Png, & Isaac, 2020; Roberts, Yaida, & Hanin, 2022). The missing aspects in these studies are generally related to the impact of these new AI technologies on organizations and businesses (Chen et al., 2021). Therefore, in this research, we will focus on context of AI technologies and business perspective.

2.1.2 AI history

AI has a much longer history than generally recognized. Its history even dates back to ancient Greece (Dennehy, 2020). However, the modern definition of AI owes much to Alan Turing and a 1956 conference at Dartmouth College, where John McCarthy officially coined the term as “the science and engineering of making intelligent machines” (Collins et al., 2021, p.2).

When the industrial computer was first developed in the 1940s, people soon realized that besides numerical calculation, it could do a wide range of intellectual activities that are typically thought to need human intelligence (Wang, 2019). This insight triggered the development of artificial intelligence more and in 1940, the term "giant brains" was widely used (Buchanan, 2005).

Especially in 1950, Artificial Intelligence development reached one of its turning points due to Turing's publication *Mind*, which introduced the Turing Test and the concept of programming computers to behave intelligently (Buchanan, 2005). Electronic breakthroughs in the early 20th century and the development of contemporary computers following World War II at Alan Turing's lab, Howard Aiken Laboratory at Harvard, Penn's Moore School, the IBM and Bell Laboratories led to increase in capacity for computation (Buchanan, 2005). Bahoo, Cucculelli and Qamar (2023) summarize historical development of AI by emphasizing many important turning points. The table below displays historical development of AI in 20th and 21st centuries by focusing on important turning points.

Table 1. Historical Development of Artificial Intelligence

AI Phases	Years	AI Development
Phase I - Spring (1940 - 1979): AI Birth, enthusiasm, golden years	1943	An artificial neurons model was proposed by Warren McCulloch.
	1950	Alan Turing pioneered Machine Learning.
	1955	Allen Newell and Herbert A. Simon developed the first artificial intelligence software, Logic Theorist.
	1956	John McCarthy coined the term "artificial intelligence" at the Dartmouth Conference.
	1966	The researchers placed a strong emphasis on creating algorithms.
	1972	WABOT-1, the first intelligent humanoid robot, was built in Japan.
	1979	The first AI winter ran from 1974 to 1979, at which time funding was stopped.
Phase II - Summer and Winter (1980 - 2010): AI boom and emergence of intelligent agents	1980	After the AI winter, AI returned with the "Expert System" this year.
	1981	The first national conference of the American Association of Artificial Intelligence was held at Stanford University.
	1993	Funds were stopped by investors between 1987 and 1993, which was accepted as the Second AI cold period.
	1997	Gary Kasparov, the global chess champion, was defeated by IBM Deep Blue.
	2002	For the first time, AI entered the home in the shape of a vacuum cleaner called Roomba.
	2006	AI was also used by the companies like Facebook, Twitter and Netflix henceforth.
	2011	The AI-based computer system IBM Watson won the quiz game show.
Phase III - Present (2011 - 2022): AI, deep learning and big data era	2012	Google released the "Google Now" app, which is capable of anticipating user preferences.
	2014	Chatbot “Eugene Goostman” won a competition in the “Turing Test”.
	2018	IBM's "Project Debater" debated with two experts on challenging subjects. Google has released a virtual assistant AI program “Duplex”.

Note. From “Artificial intelligence and corporate innovation: A review and research agenda” by S. Bahoo, M. Cucculelli and D. Qamar, 2023, *Technological Forecasting and Social Change*, *188*, 122264, p.2.

Besides these turning points, other important developments include the introduction of the first industrial robot, Unimate, in General Motors' production line in 1961 (Gasparetto & Scalera, 2019); Joseph Weizenbaum's creation of a chatbot capable of holding conversations in 1964 (Fellows, 2023); Sony's launch of the first pet dog, AIBO, in 1999 (Kubo, 2013); the breakthrough of deep learning in voice and visual identification after 2010; Apple's integration of Siri, an intelligent virtual assistant, into the iPhone in 2011 and Amazon's launch of Alexa, a virtual assistant for shopping tasks, in 2014 (Brill, Munoz, & Miller, 2022; Nobles et al., 2020); the introduction of GPT-3 for automated conversations in 2020; and the public testing of ChatGPT in 2022 (Jungwirth & Haluza, 2023).

2.1.3 AI challenges

New technologies generally cause disruptions in the early stages of development and deployment. Accordingly, it typically takes some time before its true worth becomes apparent (De Cremer & Kasparov, 2021). In the early stages of AI technology development, processing performance speed, memory and primitive operating systems and languages were the main limitations organizations developing such technologies faced (Buchanan, 2005).

Currently AI technologies face challenges including lack of experience in AI fields, high hardware costs, integration issues, businesses' limited control and understanding, reliance on high-quality, unbiased data, ethical concerns, etc. (Bezboruah & Bora, 2020). Especially from technical perspective high maintenance and repair costs due to the need for constant software updates and potentially expensive breakdowns; the risk of bugs and errors, which can lead to significant problems and data loss security concerns surrounding military robots falling into the wrong hands, posing threats without human judgment are among significant risks of AI (Osipov & Ulimova, 2013).

Besides the technical challenges, there are certain challenges coming from societies. A lack of transparency and explainability, moral dilemmas, alignment with human values and the requirement for strong accountability frameworks are among the issues AI faces (Trotta, Ziosi, & Lomonaco, 2023). The potential for widespread unemployment as robots replace human jobs, diminishing mental skills and fostering dependency on machines, the overarching fear that AI could ultimately replace humans and exert control over society are risks associated with the human factor (Osipov & Ulimova, 2013). Chowdhury and Sadek (2012) also point out important limitations that AI models face, such as the cumbersome trial-and-error process required for determining optimal design parameters and substantial liability issues regarding accountability in autonomous systems. Furthermore, widespread skepticism among industry professionals about AI's effectiveness in addressing real-world challenges and the ambiguous implications of the term "artificial intelligence" creating misconceptions about its practical applications and reliability are also pointed out as limitations for AI models (Chowdhury & Sadek, 2012).

Apart from the technical and societal challenges so far, the unpredictable growth rate of AI and the unforeseen changes it may bring also increase risk factor. The changes and development of AI depend on two factors; advancement in the AI’s capability on creating new programs independently and AI’s speed at automating complex tasks that human beings do currently (Makridakis, 2017). Due to this uncertainty, risks related to AI technologies not only come from technical and human-centered concerns but there is the possibility of broader source of risks (Novelli, Casolari, Rotolo, Taddeo, & Floridi, 2024).

By taking these challenges into account, there is a general question that has been widely discussed on whether implementing AI will lead to a more extensive organizational as well as structural transformation (Agrawal, Gans, & Goldfarb, 2021). Besides challenges summarized above, using AI may require innovative architectural design that starts from scratch with a new organizational structure, and because of this lengthy process, technology adoption may be slow (David, 1990). And if this is the case, the question is whether it is worth making this change or not.

2.1.4 AI benefits

One successful strategy for attaining corporate success is the use of new technology (Syeda, 2018). Throughout history, many companies have succeeded by adopting new technologies or found themselves in difficult situations for not adopting them. Whenever a new technology emerges, there have been in-depth discussions among people and companies about whether to adopt it or not and this situation changes the organization's strategy and structure (Gangwar et al.,2014; Prause, 2019; Premkumar & Roberts, 1999). Currently, the discussions are ongoing about AI technology (Chen et al., 2021; Makridakis, 2017; Phuoc, 2022).

AI is a technology with a long history. However, it is at the beginning stage to be adopted more widely, which rapidly increase due to the positive effects that AI brings (Chen et al.,2021). Artificial Intelligence delivers high accuracy with minimal errors, plays an important role in future technologies, enhances everyday life like smartphones with features like virtual assistants and navigation apps, efficiently handles repetitive and time-consuming tasks (Osipov & Ulimova, 2013).

AI technologies automate complex tasks which are currently done by humans and accelerate technological changes with new programs on its own. Like the industrial and digital revolutions taking place before the AI revolution, these automation and technological changes will dramatically shape businesses and employment which will transform how companies operate, manage employees and sell products (Makridakis, 2017).

Research involving large-scale companies, conducted by well-known consulting firms and universities, provide us with numerical data on the benefits of Artificial Intelligence. McKinsey and Company Survey (2022), shared also in Stanford University AI Index Report, demonstrates that adoption of AI has resulted in both revenue gains and expense reductions for organizations (Figure 2). As seen in Figure 2, a sizable portion of respondents reported that utilizing AI had reduced costs (42%), and increased income (59%) indicating that AI actually increases a company's profitability.

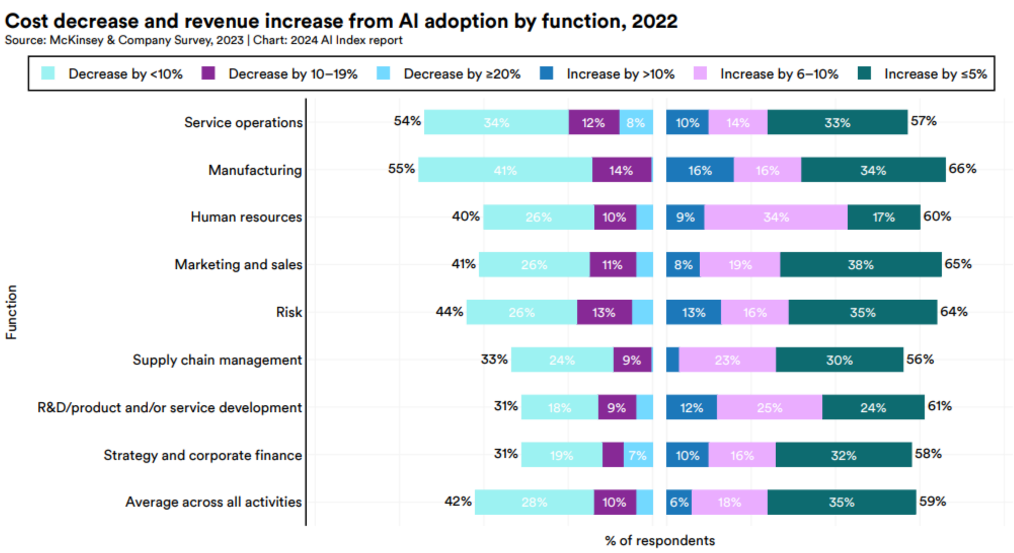

Figure 2. Cost decrease and revenue increase from AI adoption by function (Source: AI Index Report 2024)

On the other hand, Figure 3 shows the global adoption of AI by organizations based on global area. According to the survey, AI adoption increased in every area in 2023 as compared to 2022. North America maintains its leadership in AI adoption. The largest year-over-year increase was observed in Europe, the adoption rate by organizations increased by nine percentage points. China comes next with a 7% increase compared to the previous year. By automating key functions like customer services, logistics, product design and producing greater efficiency and cost savings, AI technologies will transform firms (Nguyen et al., 2022). Due to the positive developments and impacts they bring to firms, the speed and willingness to adopt these new technologies are also on the rise (Chen et al., 2021). By integrating AI into their businesses, companies will drive innovation, enhance competitive advantage and the ones who successfully embrace AI will prove to thrive and firms who fall behind will be at risk (Makridakis, 2017).

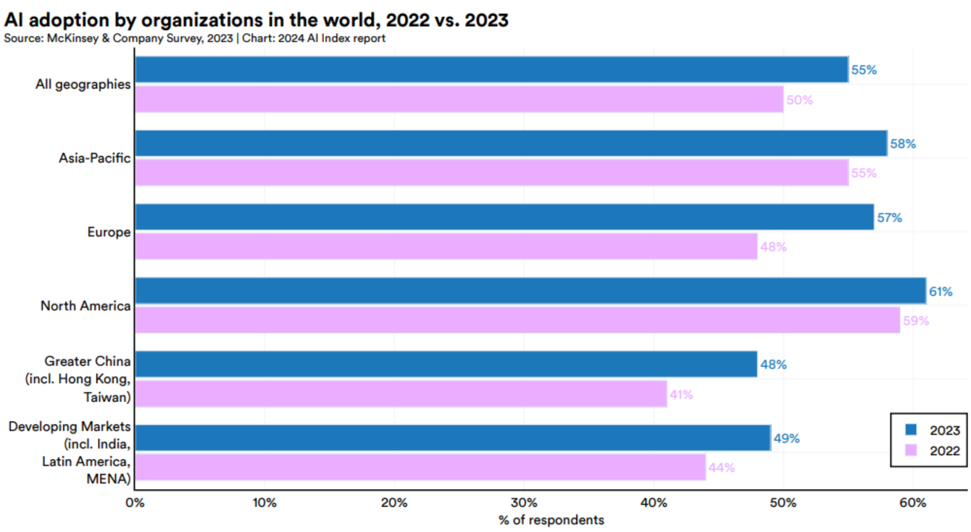

Figure 3. AI adoption by organizations in the world (Source: Index, A. I. (2024))

According to a 2023 McKinsey analysis, 55% of companies already utilize AI, especially generative AI, in at least one business unit or function, which displays an increase in usage of AI by companies compared with the result of 20% in 2017 and 50% in 2022. AI methods are particularly advantageous because AI makes it possible to have faster decision-making under uncertainty, enhance monitoring and predictive capabilities through intelligent systems, effectively handle both qualitative and quantitative data, improve security and support the development of advanced solutions to respond to various challenges (Chowdhury & Sadek, 2012). All of these ultimately drive efficiency and effectiveness across multiple applications.

PwC's Global Artificial Intelligence Study: Exploiting the AI Revolution (see Figure 4) displays important results. Based on 300 AI use cases, the report indicates that AI technologies will support up to 26% in GDP for local economies from AI by 2030, and as a result of AI global GDP could be up to 14% higher, equivalent of an additional 15.7 trillion, 6.6 trillion coming from increased productivity and 9.1 trillion coming from consumption side effects. If this happens, it could be accepted as the biggest commercial opportunity today.

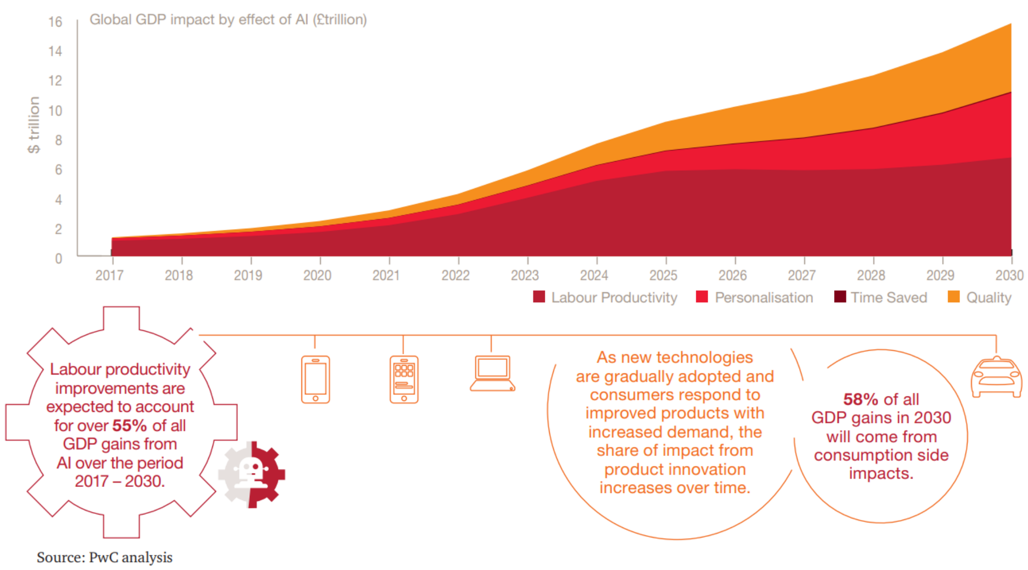

Figure 4. Global GDP impact by effect of AI (Source: PwC Global Artificial Intelligence Study: Exploiting the AI Revolution)

Software and system developers have been pushed by developments in Artificial Intelligence to create new strategies, which could lead to improvement in organizational effectiveness, raising profits, reducing expenses and so on. Businesses have successfully used this knowledge to obtain a competitive edge over their rivals and find it essential for strategic planning (Varian, 2018). Using new technology is a tried-and-true method for business success (Alsheibani, Cheung, & Messom, 2018; Nguyen et al., 2022). However, companies seeking to integrate AI into their operations or offer AI services encounter many obstacles, which need to be overcome.

2.1.5 AI adoption

Artificial Intelligence is a broad set of advanced technologies that aim to deliver particular benefits including enhanced business value and competitive advantages (Enholm, Papagiannidis, Mikalef, & Krogstie, 2022). The adoption of AI refers to systematically integrating AI-driven technologies into organizational systems, workflows, and decision-making strategies. By embracing this transformation, organizations enable to use AI-driven solutions like machine learning and analytics (Khanfar, Kiani Mavi, Iranmanesh, & Gengatharen, 2024). The adoption of AI demonstrates its significance by automating tasks, reducing errors, analyzing large dataset, and providing data driven solutions for strategies (Kehayov, Holder, & Koch,2022). It ensures operational efficiency, foster innovation and progress.

However, despite these benefits, AI adoption also presents challenges including the difficulty of integrating AI systems into existing infrastructures as a new technology, data availability problems, effective understanding problems and lack of qualified experts who can implement and manage these technologies (Straub et al.,2023). Therefore, the adaptation process contains complexity. First of all, one of the complexities of AI adoption comes from embedding AI technologies to older infrastructure, obsolete software systems, and poor data sources within existing technologies (Davenport & Ronanki, 2018). Especially, poor-quality data or the unavailability of sufficient datasets can negatively impact AI implementation (Brynjolfsson & McElheran, 2019). Furthermore, the effective implementation of AI depends on expertise in areas like machine learning and data science, but the global skills shortage continues to limit progress (Bughin, Seong, Manyika, Chui, & Joshi, 2018). Morover, high costs related to AI technology acquisition, infrastructure upgrades, and uncertainity in returns are major obstacles, often preventing organizations from fully committing to extensive AI initiatives (Bughin et al.,2018).

Nevertheless, the strategic importance of AI adoption remains undeniable, especially indicated in the previous section. Companies wish to adopt these new technology and related tools (Chen et al., 2021). However, the success of AI adoption depends not only technical integration but also organizational adoption like cultural adaptability and alignment with strategy (Enholm et al., 2022). In this case, it is important to focus on critical factors which effect this process to ensure successful implementation.

As companies are changing and transforming their business models and processes to get the advantages of AI, they generally encounter prevention in management, business process flows and the implementation of AI (Nortje & Grobbelaar, 2020). AI brings new problems and questions for firms like which aspects need to be considered while choosing whether or not to employ Artificial Intelligence applications. Therefore, the objective of this research is to determine the scope of components and dimensions that will help businesses integrate AI into their organizational structures. The results are meant to help AI application project managers and practitioners in developing policies and focusing on relevant contextual factors that facilitate effective AI application adoption, given the significance of AI application adoption in today's organizations and the future.

2.2 Theoretical framework for AI adoption

2.2.1 Diffusion of Innovation Theory

Research on the diffusion of innovations dates back to the early 1940s (Ryan & Gross, 1943). Innovations can include new practices, programs, products, services, plans, structures, or administrative systems that can be perceived and accepted as new by an organization or society (Rogers, 1983).

One of the important theories that has been widely used in innovation diffusion, which refers to how innovations spread among individuals or organizations over time, is Diffusion of Innovation Theory by Rogers (1983). Diffusion of Innovation Theory (DOI) has its roots actually in communication and describes the process by which a concept, product, service becomes popular and gradually expands among a certain population or social structure. According to Rogers (1995), those who adopt innovations early on show different traits than others who adopt them later. Adoption has been defined in various ways. In some studies, definition of adoption includes creation, implementation of technologies and development (Al-Somali, Gholami, & Clegg, 2010; Damanpour, 1991).

The adoption of innovation in an organization is explained based on five proposed qualities by Rogers (1983). The factors are as follows: 1) relative advantage, which measures how much an innovation brings improvement compared to others; 2) compatibility, which measures how well innovations can be integrated into current systems, processes, practices, and values; 3) complexity, which measures difficulty for using this innovation; 4) observability, which measures how visible the innovation is to others; and 5) trialability, which measures how simple it is to test (Rogers, 1983).

It is important to note that technology features and people' opinions about the invention are the main sources of DOI theory. Here, the organizational perspective and features are lacking points. It must be considered that the complexity of an organization surpasses the complexity of an individual (Oliveira et al., 2014).

2.2.2 Technology-Organization-Environment (TOE) framework

To explain the innovation process within a company, Tornatzky and Fleischer (1990) introduced the Technology-Organization-Environment (TOE) framework. The theory describes how technical and environmental elements influence organizations' decisions about adopting technological innovations at the organizational level.

According to Tornatzky and Fleischer (1990), the Technological, Organizational, and Environmental contexts are the three elements of a firm's setting that have an impact on the process of a technological innovation. The TOE is thought to be a more company perspective and sense for the investigation of innovation adoption at the organizational level, as many authors point out in the literature (Amini & Bakri, 2015; Chen et al., 2021; Nguyen et al., 2022; Yang, Kankanhalli, Ng, & Lim, 2013).

The impact of three factors, which are organization, technology, and environment, are deeply analyzed on the adoption of innovation. The technology context refers to both internal and external technologies that are vital to the company and may be adopted. The features of a company like company size, managerial structure, resources, and communication channels are all referred to as the organizational context (Nguyen et al., 2022). The market, competition, regulatory environment are examples for the environment context (Chen et al., 2021).

There are several theoretical frameworks that focus on technology acceptance and its adoption process. Technology Acceptance Model (TAM) (Davis, Bagozzi, & Warshaw, 1989), Unified Theory of Acceptance and Use of Technology (UTAUT) (Venkatesh, Morris, Davis, & Davis, 2003), Theory of Planned Behavior (TPB) (Ajzen, 1991) and Social Cognitive Theory (SCT) (Bandura, 1986) are among these theories. Rather than relying on other common technological acceptance ideas, this research focuses on the TOE framework for several key reasons. In keeping with the organizational focus of this study, TOE first distinguishes itself from previous theories and models by concentrating on technological acceptance at the company level (Hradecky, Kennell, Cai, & Davidson, 2022). Furthermore, the Technology-Organization-Environment (TOE) framework takes into account not only the acceptance of technology but also the organization and environment dimensions, which generally have a direct impact on the adoption process. These dimensions evaluate the resources and characteristics of the firm in the external business environment. Thanks to TOE framework's approach that encompasses the technological, organizational, and environmental dimensions, it has been widely used in new technology acceptance studies like cloud computing (Oliveira, Thomas, & Espadanal, 2014), Big Data Analytics (Mwemezi & Mandari, 2024), and Blockchain technology (Malik, Chadhar, Vatanasakdakul, & Chetty, 2021). Numerous studies using the TOE framework confirmed that the theory led to studies providing reliable results in information technology acceptance and adoption (Amini & Bakri, 2015; Chen et al., 2021; Malik et al., 2021; Nguyen et al., 2022; Oliveira et al., 2014).

In the case of AI, its use and adoption has not been thoroughly studied, especially when it comes to organizations. The aim of the research is to determine how prepared a company is to embrace AI, therefore examining the three TOE dimensions provides a deep understanding of elements that affect a firm's willingness to adopt AI and the success of the implementation process. It highlights the particular environment in which the adoption process takes place, and it can be used to assess the factors influencing AI adoption (Nguyen et al., 2022). By considering all the reasons mentioned above, the TOE framework could be evaluated as suitable to start when looking at AI adoption.

2.2.3 Combining DOI and TOE frameworks

The TOE viewpoints and Roger's list of innovation qualities are similar in many aspects and complement each other. As a result, it is widely acknowledged that adding the TOE contexts to the DOI theory has benefits and numerous IT adoption studies have made use of DOI and TOE, which have consistently received empirical support (Alkhalil, Sahandi, & John, 2017; Amini & Bakri, 2015; Chen et al., 2021; Hasani, O'Reilly, Dehghantanha, Rezania, & Levallet, 2023; Liu, 2019).

The two theories, DOI and TOE framework, differ significantly from one another as well. The function of individual traits (such as top management support, leadership) is not specified by TOE (Oliveira et al., 2014). In this case, the DOI theory recommends including top management support and other individual constraints inside the organizational framework. In a similar manner, DOI ignores the significance of the external environment (Chen et al.,2021). Due to DOI's limitations, the technology, organization, and environment contexts included in the TOE framework contribute to a more thorough understanding of IT adoption. Thus, theories meaningfully reinforce one another, and so in this research, both of them have been used.

CHAPTER 3

RESEARCH MODEL AND HYPOTHESES

This chapter explains hypotheses and research model. In the hypotheses part, the hypotheses formulated within our research are outlined. In the second part, the research model is explained, the model has been visualized and a graphical representation included.

3.1 Hypotheses development

As previously mentioned, there are publications concerning theories and applications of AI in the literature. On the other hand, little is known about the enabling factors that lead to the adoption of AI by organizations and how these factors interact and impact their decision to implement AI. In order to investigate the important elements that influence AI adoption at the organizational level further, this study suggests a research model by combining the TOE framework and DOI theory.

Based on the theories used, the constructs to be analyzed in this research are classified in three main dimensions: technical dimension, organizational dimension, and environmental dimension. Technology dimension includes Compatibility, Relative Advantage, and Perceived Risk. Organizational dimension covers Managerial Capability, Managerial Support, Technical Capability, and Data Management. Competition’s Pressure, Vendor Partnership, Market Uncertainty are the constructs for Environmental dimension.

3.1.1 Technological dimension

Technological factors refers to the attributes and capabilities of the technology itself which influence organization's decision to adopt and implement it. By understanding these technological factors, organizations better assess whether new technologies can be adopted into their current systems and ensure smoother as well as more effective implementation. To explore factors in technological dimension, both DOI and TOE frameworks provide valuable insights. Five innovative traits are identified by Rogers (1995) in the DOI theory. Compatibility, relative advantage, trialability, intricacy, and observability are these traits. However, many studies indicate that the first three factors—compatibility, relative advantage, and complexity—are regarded as being systematically associated at the organizational level (Chen et al., 2021; Tornatzky & Fleischer, 1990; Wu, Wang, & Lin, 2007). Therefore, these three factors are selected for this research at the beginning, but complexity was excluded during the process due to reliability analysis results. Furthermore, based on the literature review, perceived risk is also evaluated as a variable that could have an impact on AI adoption because this factor influences acceptance and willingness to adopt new technologies (Mwemezi & Mandari, 2024). Finally, the constructs of relative advantage, perceived risk and compatibility fall under the technological dimension in this research.

3.1.1.1 Compatibility

According to Rogers (1995), compatibility refers to how well an invention may meet the demands of potential adopters while providing value and experience. According to DOI theory, innovation adoption is strongly correlated with an invention's ability to fit experiences and needs (Chen, 2019; Rogers, 1995). The literature reveals a favorable relationship between technology adoption and compatibility (Wu et al., 2007). Any new technology adoption may alter company procedures and practices, which can lead to opposition to the adoption (Hasani et al., 2023). Chen (2019) proposes that in the case of AI technologies adoption, more compatibility leads to faster adoption. AI technology implementation will probably be less costly and time-consuming if it is compatible with current IT settings. Therefore, AI may be accepted more quickly (Nguyen et al., 2022). Hence, the following hypothesis is proposed:

Hypothesis 1: Compatibility is positively associated with the Adoption of AI.

3.1.1.2 Relative advantage

An organization's desire to adopt innovative technology is influenced by how innovation is considered to be beneficial, according to Rogers (2003). The relative advantage of innovation is the extent to which it is considered as being superior to the technology that it replaces (Nguyen et al., 2022). According to Yang et al. (2013) and du Plessis and Smuts (2021), an organization's willingness to accept new technology is impacted by the perceived advantage of innovation. New technologies with distinct and obvious benefits in fostering strategic and operational performance are more likely to be accepted (Greenhalgh, Robert, Macfarlane, Bate, & Kyriakidou, 2014). AI applications save operating costs, raise efficiency, boost customer satisfaction, and improve service quality for enterprises. In other words, innovative technology will spread more quickly if its perceived relative benefit is greater (Chen, 2019). Therefore, a subsequent hypothesis is put forward:

Hypothesis 2: Relative Advantage is positively associated with AI Adoption.

3.1.1.3 Perceived risk

Perceived risk refers to the skepticism of the potential disadvantages of utilizing a service or product associated with adopting a technology (Alyoussef & Al-Rahmi, 2022; Liu & Tao, 2022). It is taken into account before identifying the extent and potential uncertainties associated with new technology adoption (Mwemezi & Mandari, 2024).

In the context of adopting new technologies, perceived risk often includes concerns about reliability, cost, social acceptance, training and operational difficulties (Zerfass, Hagelstein, & Tench, 2020). If the perceived risk is high, individuals and organizations generally hesitate or resist adoption and tend to overlook expected benefits (Stjepić, Pejić Bach, & Bosilj Vukšić, 2021). Risk serves as a significant barrier to technology adoption, which is also considered for AI adoption where rapid advancements and ethical uncertainties decrease trust factor (Novelli et al., 2024). Users evaluate concerns about unintended consequences, not understanding deep-logic, and losing control over decision-making process (Carrasquilla-Díaz, De Luque-Pisciotti, & Lagos-González, 2024). Furthermore, due to AI's complexity related to dependence on data, difficulty in adoption, organizational readiness, hesitation for adoption increase and thus higher perceived risk creates a barrier for adoption (Mwemezi & Mandari, 2024). Therefore, at the organizational level AI technology will spread more slowly if its perceived risk is high. As a result, a hypothesis that follows is proposed:

Hypothesis 3: Perceived risk is negatively associated with AI Adoption.

3.1.2 Organizational dimension

Organizational factors refer to internal aspects and resources of the organization like management, organizational culture, resource availability and leadership support. These qualities are unique, cannot be transferred and ingrained inside an organization (Phuoc, 2022). Organizational factors are crucial because it examines how the internal characteristics of an organization influence adoption and implementation of new technologies (Tornatzky & Fleischer, 1990). Based on the literature review on AI adoption, the constructs of managerial capability, managerial support, technical capability, data management and organizational readiness were selected (Chen et al. 2021; Phuoc, 2022; Stjepić et al., 2021). However, organizational readiness was excluded during the analysis process due to reliability results. Therefore, the impact of remaining four factors on AI adoption was investigated.

3.1.2.1 Managerial capability

The term managerial capability describes a manager's ability to encourage, inspire and empower employees to the efficiency and growth (House, Javidan, Hanges, & Dorfman, 2002). Strong managerial capabilities play a pivotal role in adoption and new technology can be swiftly adopted in business processes and organizations (Soomro, Fan, Sohu, Soomro, & Shaikh, 2024). It is essential for the successful adoption process because it significantly impacts an organization’s ability to recognize, execute, and integrate technological and organizational resources into processes (Agrawal, 2017). This capability includes for formal education and training, project team management, effective internal communication and cooperation in order to promote the adoption of AI (Chen et al., 2021).

Strong managerial capability ensures AI adoption and addresses the challenges that accompany such transformations (Soomro et al. 2024). Organizations with strong managerial capabilities are better positioned to overcome the challenges of AI adoption (Phuoc, 2022). According to Emmelhainz (1988), organizational resistance to change is the primary barrier to the adoption of new technology. In his research, it is highlighted that resistance to IT adoption as a major challenge, often stemming from a lack of understanding, fear of job displacement, and ambiguity regarding the benefits of new technologies (Emmelhainz, 1988). This resistance can be resolved through strong managerial capabilities (Nguyen et al., 2022). For successful technology adoption, effective communication, achieving strategic goals and plans, and ensuring organizational-wide education and training can be made possible through effective management (Chen et al., 2021). Thus, the subsequent hypothesis is proposed:

Hypothesis 4: Managerial capability is positively associated with the Adoption of AI.

3.1.2.2 Managerial support

Effective technology adoption requires management support since it indicates how much managers understand and value a new technology system's technological capability (Maroufkhani, Wan Ismail, & Ghobakhloo, 2020). Because top management controls resource allocation and service integration, managerial support is essential to any major organizational transition (Co, Eddy Patuwo, & Hu, 1998). When it comes to introducing next-generation technology to businesses, top management is crucial (Amini & Jahanbakhsh Javid, 2023; Sayginer & Ercan, 2020; Sugandini, Margahana, & Rahatmawati, 2020).

According to Singh, Gupta, Busso and Kamboj (2019), organizations that want to implement new technologies must have the backing of senior management, which makes judgements about important updates. When leaders see the value of new technology, they will probably set aside funds to support its implementation and persuade other members of the firm to follow suit (Oliveira et al., 2014). In order to incorporate the newest technology within an organization, top management must come up with a plan, supply the necessary funds, and assist staff members as they do so. Consequently, the following theory is proposed:

Hypothesis 5: Managerial support is positively associated with AI Adoption.

3.1.2.3 Technical capability

The term technical capability describes the tangible resources necessary to adopt a technology—like computer hardware, data, and networking, and intangible assets including technical expertise, IT development and collaboration techniques, and application procedures that can successfully incorporate new technologies (Aboelmaged, 2014; Garrison, Wakefield, & Kim, 2015). These technical capabilities are critical in the context of AI adoption, as organizations must have the right resources and expertise to effectively implement AI systems. Technical proficiency—the capacity to effectively oversee and apply resources—directly effects an organization’s success in adopting AI and gaining a competitive advantage (Nguyen et al., 2022). Strong technical capability makes integration simpler and enables the IT department to provide AI solutions quickly and effectively.

Superior technical talents increase a company's likelihood and speed of using the complex nature of novel technologies, giving it a competitive advantage over rivals (Schmitt, Mladenow, Strauss, & Schaffhauser-Linzatti, 2019). Companies achieve effective adoption, if they can incorporate new AI technologies into its current IT infrastructure more quickly. As a result, the following hypothesis put out below:

Hypothesis 6: Technical capability is positively associated with AI Adoption.

3.1.2.4 Data management

Data plays a central role in driving innovation, improves efficiency, and fosters growth. Thus, using data in many fields and its growing importance have made it a key resource for both societies and businesses. In today's competitive business environment, data is crucial for informed decision-making, gaining customer insights, and crafting effective strategies. As highlighted by Brynjolfsson and McAfee (2014), data is now a key driver of business innovation, enabling organizations to make informed decisions, optimize processes, and ensure a competitive advantage.

There is a critical relationship between data and the business processes that produce and use it (Uren & Edwards, 2023). Adoption of data-dependent technologies strictly depends on data management because these data-driven systems can be affected by data definition, control database modeling and operation, establish data standards, permit data security, and guarantee enterprise reliability and trustworthiness for data management (Ramamurthy, Arun, & Atish, 2008). Mariani and Wamba (2020) argue the importance of partnering with data to enhance decision-making, optimize operations, and gain a competitive edge for firms. Better data management is also expected to increase the likelihood of adoption for data-driven systems (Stjepić et al., 2021). As a result, the following hypothesis put out below:

Hypothesis 7: Data management is positively associated with AI Adoption.

3.1.3 Environmental dimension

Environmental dimension refers to external influences like industry competition, regulatory frameworks, and the availability of vendor support or partnerships (Tornatzky & Fleischer, 1990). These external elements are shaped by the broader ecosystem within which organizations operate. They may either encourage or discourage businesses from adopting innovative technologies (Tornatzky & Fleischer, 1990). Therefore, as a result of insights gathered from the literature, competition's pressure, market uncertainty and vendor partnership were selected in this research (Chen et al. 2021; Nguyen, 2022).

3.1.3.1 Competition's pressure

According to Al-Jabri and Alabdulhadi (2016), competition's pressure is the degree to which a company embraces new technology in response to pressure from competitors. Yenipazarli (2019) also describes it as the level of competition an organization encounters from competitors in its market.

Businesses encounter pressure when rivals embrace certain new technology. To remain competitive, they generally implement new technology right away (Chen et al., 2021). Innovation in information technology has the power to transform the competitive landscape, modify industrial structures, and create new strategies for doing better than competitors (Porter & Millar, 1985).

When faced with pressure from competitors, businesses are more likely to respond swiftly and monitor competitor behavior (Hasani et al., 2023). Businesses that are under this pressure need to implement new technology more quickly. It has long been known that competition intensity is a key factor in the adoption literature, as seen by the numerous research studies that have focused on its significance (Al-

Somali et al., 2010; Zhu, Kraemer, & Xu, 2003). Thus, the following hypothesis is put forth:

Hypothesis 8: Competition's pressure is positively associated with AI Adoption.

3.1.3.2 Vendor partnership

Vendor support includes system upgrades, vendor or consultant-provided technical training, and aid throughout implementation and adoption (Chatzoglou, Chatzoudes, Fragidis, & Symeonidis, 2017). Many companies prefer outsourcing solutions in various technological areas and they continue to rely on vendor support for the services they receive. Artificial intelligence is a rapidly developing technological field. It is characterized by significant challenges and complexity, thus, there is a high demand for technical supports of vendors to address these challenges (Chen et al., 2021).

Vendors have significant effect on deployment of AI technologies, and they must work closely with their clients (Nguyen et al., 2022). Furthermore, there is a lack of skilled experts in this field due to its rapid development and complexity, which also increases the importance of vendor partnership (Chen et al.,2021). Thus, we can emphasize that vendor support and technology adoption are associated. As a result, the following hypothesis put out below:

Hypothesis 9: Vendor partnership is positively associated with AI Adoption.

3.1.3.3 Market uncertainty

Many studies based on Technology-Organization-Environment (TOE) framework have consistently highlighted the significance of market uncertainty on new technology adoption (Cao, Baker, Wetherbe, & Gu, 2012; Chau & Tam, 1997; Chen, 2019). Market uncertainty, driven by factors, such as technological changes, fluctuating competition, shifting demands, supply instability, and political dynamics, creates a challenging environment for organizations (Chau & Tam, 1997).

Companies are faced with challenges in responding to a rapidly changing uncertain business environment (Prause, 2019). This uncertain environment compels organizations to seek out innovative solutions to maintain a competitive edge. It intensifies need for AI adoption and making it even more crucial for organizations. In this context, AI technologies and their adoption have shown significant promise to help businesses to remain competitive (Chen et al., 2021). Especially in industries with rapid technological advancements, AI adoption can be seen as essential to stay competitive (Liu et al., 2021).

Therefore, AI applications have become increasingly critical, not only for operational efficiency but also for capitalizing on new market opportunities and maintaining competitiveness (Chen, 2019). As a result, the unpredictable nature of the market accelerates the push for AI adoption, as companies seek to leverage these technologies to stay ahead of the competition. Thus, the following hypothesis was proposed below:

Hypothesis10: Market uncertainty is positively associated with AI Adoption.

3.2 Research model

The purpose of this thesis is to analyze the critical factors that support businesses in adopting AI, and to explore how these factors combine and interact with one another and with AI itself. In this regard, the key aspects of organizational technology adoption as outlined by the TOE and DOI theories were considered.

As outlined above, drawing from research on the new technology adoption, TOE framework and DOI theory, relevant constructs were addressed. Through investigating these constructs that impact diffusion of artificial intelligence technologies, an area not yet fully explored in the literature, we seek to make a valuable contribution to both academic studies and real-world business applications. The theoretical framework of this thesis is presented in Figure 5. In this research, the independent factors are classified into three categories, namely organizational dimension, technological dimension, environmental dimension, whereas AI adoption is considered as a dependent variable. Figure 5 below shows our research model.

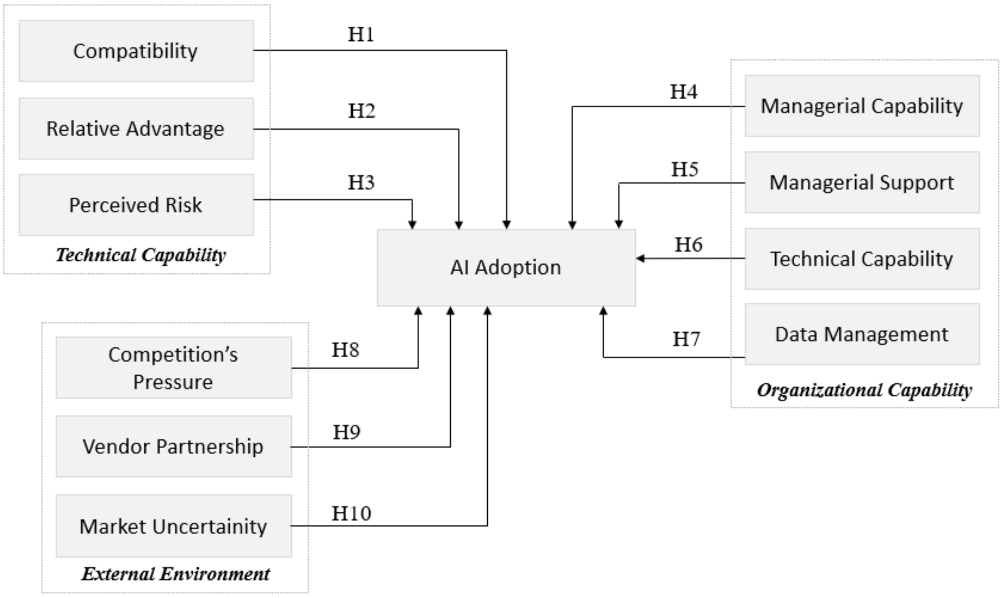

Figure 5. Research model for AI adoption

CHAPTER 4

RESEARCH METHODOLOGY

This chapter outlines the thesis's methodology. This thesis's general direction is established by first outlining the study goal. Then, the research strategy and methodology are explained. After that, data gathering is provided, and the data analysis is explained.

4.1 Quantitative research method

In this research, quantitative research method is used. Quantitative research refers to a systematic approach for investigation of a phenomena by collecting and analyzing numerical data, thus allowing researchers to identify relationships, patterns, and causal links between variables (Mohajan, 2020). By using quantitative research method, it is possible to understand large-scale trends, predict outcomes, and verify theories. This method relies on structured tools such as surveys, experiments, and observations to gather measurable data that can be analyzed statistically.

4.2 Data collection method

In this study, an online questionnaire created with Google Docs was used to collect data. Participants in this survey were contacted between July 2024 and September 2024. It was sent to a group of knowledgeable people with experience in the field of Artificial Intelligence and Information Technology. The survey was based on validated scales and published literature (see Appendix A). Its link was sent to the participants through email. The constructs were measured using a seven-point Likert scale on an interval level ranging from "strongly disagree" to "strongly agree". The URL for the questionnaire was sent to the participants via social networking sites, and they were told to share it with their connections. Furthermore, one of the most well-known crowdsourcing sites, the cloud research platform, shared the questionnaire link. We gathered total of 131 responses. Participants joined the survey on a voluntary and anonymous basis.

4.3 Components of the questionnaire

In this research, the survey intended to gather information about AI adoption serves as the main research tool. The eleven latent components in the framework are as follows: Vendor Partnerships, Data Management, Market Uncertainty, Competition's Pressure, Top Management Support, Technical Capability, Managerial Capability, Compatibility, Relative Advantage, and AI Adoption. Due to reliability and validity results two components namely Organizational Readiness and Complexity were deleted; however, the related questions could be seen in Appendix A and B, survey questions parts. The original scale language is English, the Turkish version has been obtained through translation and then retranslated back into English to ensure that the original meaning was preserved. Thus by using back translation method, which involves comparing the back-translated version with the original to identify inconsistencies, it is ensured that the translation accurately conveys the intended meaning across cultures (Brislin, 1970). Appendix A contains the questionnaire in English, while Appendix B has it in Turkish.

Items from earlier research on information technology, innovation, new technology acceptance, new technology implementation as well as diffusion were selected to create the questionnaire. The questions and scales applied in this research have been previously used in various sources in the literature, and their validity and reliability have been tested in each research. Appendix D displays survey questions based on constructs and sources for each construct.

4.4 Research measurement model

Partial Least Square (PLS) is used in this work to assess model fit and analyze research data. Researchers are drawn to the Partial Least Square technique as a statistical method for testing structural equation modeling due to various advantages: First of all, smaller sample size could be used compared to other methods. Secondly, it does not require normally distributed data. It can also manage formative as well as reflective constructs. It serves as a powerful tool for theory development and validation, particularly when research focuses on emerging or evolving theoretical frameworks, providing a flexible and reliable method for testing relationships and refining constructs. Furthermore, PLS can be applied to complex models with many constructs and their relations. Additionally, PLS is particularly useful for predictive analysis, which makes it a powerful tool for researchers.

Due to these advantageous, PLS-SEM analysis is attractive to researchers. As a result of being “distribution - free” normality assumption is not required (Chin, 1998). In addition, PLS produces estimations of Latent Variable for every instance in the data collection (Urbach & Ahlemann, 2010). According to Fornell and Bookstein (1982), PLS will not result in factor indeterminacy or give unacceptable solutions. Lastly, independent observations or residuals with the same distributions are unnecessary (Chin & Newsted, 1999; Lohmöller, 1989; Wold, 1980).

Partial Least Square was preferred due to reasons mentioned above, particularly because the number of people working with and using AI is limited, coming from the fact that AI is a new technology. The WarpPLS tool is used to examine the measurement model and structural model in this investigation. While the structural model displays the possible causal linkages between the latent variables, the measurement model illustrates the relationships between the constructs (latent variables) and their indicators (observed variables) (Urbach & Ahlemann, 2010)

4.5 Research quality and ethics

Boğaziçi University Human Subjects Review Committee granted permission to perform this study (see Appendix C). The goal of the study, its scope, the name of the institution, the name of the research, the email address of the researchers, the anticipated time required to complete the survey, the level of risk (if any), and any duties related to the study are all disclosed in the instructions. Additionally, participants are informed that participation in this survey is completely voluntary, and that no sensitive or personal information is needed. Participants also get guarantees of anonymity and confidentiality.

CHAPTER 5

ANALYSIS AND RESULTS

This chapter examined research results using reliability, validity and correlation analysis. The comments in this chapter are the outcome of the presentation of the analytical results.

5.1 Demographic profile of the respondents

The target population for this study is AI users, IT specialists, and managers working on AI services and products. Total number of respondents is 131 people. Demographics of respondents are given in Table 2. About 55.73% of those who participated in the research were male, while 43.51% were female. In terms of age groups, most of them are in the 30-35 years with 37.4%. Then, it was followed by respondents with the age of 36-45 years with 25.19% and the age of 24-29 years with 24.43%.Regarding the level of education, 54.2% of the users were "Graduated from a University" and it is followed by "Master’s/PhD. Graduate" with 26.72% and "Master’s/PhD. Student" with 15.27%.

Table 2. Demographic Profile of Respondents

Gender	Female	Male	Others			
	57 43.51%	73 55.73%	1 0.76%			
Age	<24	24-29	30-35	36-45	46-55	56-65
	5 3.82%	32 24.43%	49 37.40%	33 25.19%	7 5.34%	5 3.82%
Education	University Student	University Graduate	Master's /PhD Student	Master's /PhD Graduate		
	5 3.82%	71 54.20%	20 15.27%	35 26.72%		

Participants were also asked questions regarding their company and position, including company size, their current positions, total years of work experience, industry and how many years they have been in their current role. About 29.77% of respondents are in the technology, media and telecommunications industry, 25.95% are in the transportation and logistics industry, and 22.14% of them work at financial services, respectively.

The question regarding company size focused on the number of employees. About 55.73% of participants work in companies with over 2000 employees, 18.32% are in companies with between 500 and 2000 employees, and 15.27% of the participants are employed by companies with fewer than 100 employees. The participants are also asked for the organization's location where the Artificial Intelligence product/service was adopted. Participants responded to this question with 61.83% from Turkey, 19.85% from the USA, and the remaining portion from other countries.

The current job positions are divided into four main categories: AI users, IT specialists, managers, and others. Among the participants, 38.17% work as IT specialists, 40.46% are AI users, and 28% are managers.Participants having 15 years or more of total work experience are about 19.08%, 25.95% have between 10 and 15 years of experience, and 22.14% have between 5 to 10 years of total experience. Regarding the years of work experience at companies that employ AI products or services, the results show that 26.72% of participants have 5-10 years of experience, total of 19.85% have between three to five years, and 38.17% have less than three years of experience. Table 3 below displays the results in detail.

Table 3. Company and Work Experience

Industry	Technology, Media and Telecommunications	Transportation and Logistics	Financial Services	Others	
	39 29.77%	34 25.95%	29 22.14%	29 22.14	
Company Size	< 100 Employees	100 - 499 Employees	500 - 2000 Employees	> 2000 Employees	
	20 15.27%	14 10.69%	24 18.32%	73 55.73%	
Country	Turkey	USA	Others		
	81 61.83%	26 19.85%	24 18.32		
Current Position	AI Product/Service User	IT Specialist	Manager		
	53 40.46%	50 38.17%	28 21.37%		
Position Work Experience	< 3 Years	3 - 5 Years	5 - 10 Years	10 - 15 Years	> 15 Years
	50 38.17%	26 19.85%	35 26.72%	12 9.16%	8 6.11%
Total Work Experience	< 3 Years	3 - 5 Years	5 - 10 Years	10 - 15 Years	> 15 Years
	20 15.27%	23 17.56%	29 22.14%	34 25.95%	25 19.08%

5.2 Data analysis and results

Individual item reliability, construct validity, convergent validity, discriminant validity of the measurement tool and non-response bias analysis are examined in order to determine the suitability of the measurement model. In the suggested model, 10 constructs (factors) and associated observable variables (indicators) are measured. Normally, the research started with the aim of testing twelve constructs mentioned in Appendix E. However, two constructs namely “Complexity” and “Organizational Readiness” were removed from the analysis due to their reliability and validity results that we reached in the first analysis.

After this exclusion process, we are left with ten constructs to analyze. Besides this elimination, Managerial Capability 1(MCAP1), Managerial Capability 2(MCAP2), Manager Support 1(MSUP1), Manager Support 2(MSUP2), Market Uncertainty 1(MUNC1), Market Uncertainty 3(MUNC3), AI Adoption 4(ADOP4), and AI Adoption 5(ADOP5) have been deleted due to their reliability results, thus this adjustment allowed for more accurate outcomes. For Market Uncertainty and Managerial Capability constructs, after removing problematic items, only two items remain for each construct. Although three items are typically considered the minimum for measuring a construct, in some cases due to reliability results, two items may be used (Hinkin, 1995).

5.2.1 Measurement model

By taking certain threshold values into account, the analysis results’ reliability is ensured. In case of factor loadings, 0.5 is a threshold and this value and above is considered as strong (Hair, Black, Babin, Anderson, & Tatham, 2006). In this research, all variable results are above value. Appendix E displays that combined loadings for them are above 0.5, ranging between minimum 0.758 and maximum 0.965.

Cronbach’s Alpha and composite reliability are other measurements that are carefully reviewed as they are important to ensure reliability and internal consistency. In the case of Cronbach’s Alpha, results only above 0.7 are accepted (Gliner & Morgan, 2000). The lowest Cronbach’s Alpha value in the research is 0.729 while the maximum value is 0.956. The table below demonstrating Cronbach’s Alpha values indicates that in terms of reliability all the constructs are within an acceptable range. On the other hand, composite reliability values are also carefully reviewed and threshold 0.7 is accepted as a strong value (Shrestha, 2021). Composite reliability results starting from a minimum value of 0.8, which is higher than 0.7 threshold has proven once again that the analysis results are reliable and reinforces Cronbach Alpha results.

Variance Inflation Factor (VIF) is a criteria used for analyzing the possibility of multicollinearity in analysis. It is recommended that VIF values should be smaller than 3.3 (Kock, 2015). In this research VIF values range from 1.415 for Managerial Capability to 3.275 for AI Adoption. This indicates that there is no risk for multicollinearity. Furthermore, this study adopts the VIFs method to evaluate Common Method Bias, with results indicating that all VIF values are below the suggested threshold of 3.3 (Kock, 2015). Therefore, the impact of CMB, as a challenge related to measurement methods relying on survey-based data collection, is minimal in this study. Table 4 displays Cronbach’s Alpha, consistency, and reliability results.

Table 4. Construct Cronbach's Alpha, Consistency, and Reliability.

Item	Cronbach's Alpha	Composite Reliability (CR)	Variance inflation factor (VIF)
Compatibility (CMPT)	0.955	0.965	1.886
Relative Advantage (RADV)	0.897	0.924	2.133
Perceived Risk (PR)	0.911	0.938	1.739
Managerial Capability (MCAP)	0.878	0.943	1.415
Technical capability (TECC)	0.843	0.895	3.009
Managerial support (MSUP)	0.940	0.962	2.720
Market Uncertainty (MUNC)	0.729	0.881	2.353
Data Management (DATA)	0.858	0.904	2.078
Competition's Pressure (CP)	0.827	0.897	1.535
Vendor Partnership (VENP)	0.893	0.922	1.532
AI adoption (ADOP)	0.956	0.972	3.275

For a valid discriminant validity, Average Variance Extracted (AVE) values' square roots must be greater than the correlations of that variable with all the factors in the model. The AVE value for Compatability is 0.920; for Relative Advantage is 0.842; for Perceived Risk is 0.0889; for Managerial Capability is 0.944; for Technical Capability is 0.826; for Management Support is 0.945 ; for Market Uncertainty 0.887; for Data Management 0.837; for Competitive Pressure is 0.863; for Vendor Partnerships is 0.839; for AI Adoption is 0.959. Table 5 displays correlations and square roots of AVE values.

Table 5. Correlations and Square Roots of AVE Values

	CMPT	RADV	PR	MCAP	TECC	MSUP	MUNC	DATA	CP	VENP	ADOP
CMPT	(0.920)										
RADV	0.181*	(0.842)									
PR	-0.506**	-0.243**	(0.889)								
MCAP	0.230**	0.349**	-0.149	(0.944)							
TECC	0.570**	0.184**	-0.485**	0.363**	(0.826)						
MSUP	0.523**	0.225*	-0.551**	0.285**	0.686**	(0.945)					
MUNC	0.199*	0.696**	-0.289**	0.442**	0.293**	0.225**	(0.887)				
DATA	0.453**	0.301**	-0.324**	0.363**	0.648**	0.490**	0.359**	(0.837)			
CP	0.174*	0.442**	-0.230**	0.260**	0.163*	0.230**	0.459**	0.353**	(0.863)		
VENP	0.400**	0.113	-0.276**	0.278**	0.480**	0.462**	0.188*	0.436**	0.159	(0.839)	
ADOP	0.612**	0.366**	-0.574**	0.275*	0.633**	0.719**	0.370**	0.485**	0.394**	0.510**	(0.959)

Notes:

**. *Correlation is significant at the 0.01 level (2-tailed).*

*. *Correlation is significant at the 0.05 level (2-tailed).*

Furthermore, we conducted a nonresponse bias analysis comparing two groups in our data. The data was split into early and late respondents, and a t-test was performed using demographic variables for both groups. The results showed no statistically significant differences between two groups across demographic variables. The p-values from the independent samples t-test were consistently greater than 0.05, indicating that the means of these variables did not differ meaningfully between the groups. Levene's Test showed that the variation in most variables was similar between the groups, thus supporting assumption of homogenity. The only exception was total experience, where the variation was different. However, even in this case, the mean difference was not significant. These findings suggest an absence of nonresponse bias, thus support the representativeness of the sample, the homogeneity of the groups and the reliability of the research results. Below Table 6 displays nonresponse bias analysis results.

Table 6. Nonresponse Bias Analysis Result

Independent Samples Test

		Levene's Test for Equality of Variances		t- test for Equality of Means			
		F	Sig	t	df	Significance	
						One-sided p	Two-sided p
GNDR	Equal variances assumed	0.809	0.370	-1.573	128	0.059	0.11
	Equal variances not assumed			-1.573	127.632	0.059	0.11
AGE	Equal variances assumed	1.360	0.246	-0.025	128	0.490	0.98
	Equal variances not assumed			-0.025	126.451	0.490	0.98
INDS	Equal variances assumed	0.765	0.384	0.463	128	0.322	0.64
	Equal variances not assumed			0.463	128	0.322	0.64
EDCT	Equal variances assumed	0.290	0.591	-0.219	128	0.414	0.82
	Equal variances not assumed			-0.219	127.330	0.414	0.82
LCTN	Equal variances assumed	0.441	0.508	-1.571	128	0.059	0.11
	Equal variances not assumed			-1.570	127.015	0.059	0.11
CSIZE	Equal variances assumed	1.025	0.313	1.070	128	0.143	0.28
	Equal variances not assumed			1.071	127.966	0.143	0.28
AIEX	Equal variances assumed	0.116	0.734	0.744	128	0.229	0.45
	Equal variances not assumed			0.744	127.555	0.229	0.45
TOEX	Equal variances assumed	4.211	0.042	-0.999	128	0.160	0.32
	Equal variances not assumed			-0.997	128	0.160	0.32

5.2.2 Structural model

The research analysis can be summarized as follows: The analysis found positive and significant relationship between Compatibility and AI Adoption (β=0.22, p<0.01), Technical Capability and AI Adoption (β=0.14, p=0.04), Managerial Support and AI Adoption (β=0.35, p<0.01), Competitions Pressure and AI Adoption (β=0.18, p=0.02), Vendor Partnership and AI Adoption (β=0.18, p=0.02).

On the other hand, the analysis found positive but not statistically significant relationship between Relative Advantage and AI Adoption (β = 0.12, p = 0.08), Perceived Risk and AI Adoption (β=0.09, p=0.15) , Managerial Capability and AI Adoption (β=0.07, p=0.21), Market Uncertainty and AI Adoption (β = 0.01, p = 0.46) , Data management and AI Adoption (β=0.06, p=0.24) .

Below Figure 6 displays structural model results.

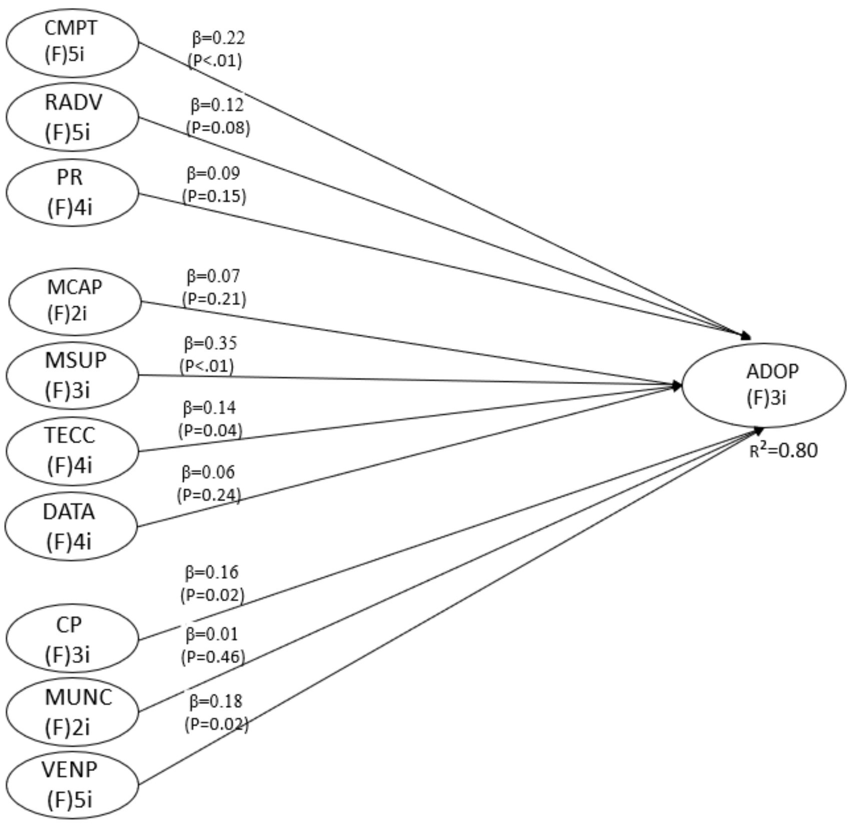

Figure 6. Structural model

Table 7 displays hypotheses tested and their status on whether they were supported or not.

Table 7. Summary of Hypotheses Test Result for the Structural Model

Hypotheses	Status
H1: The adoption of AI is positively correlated with compatibility.	Support
H2: The adoption of AI is positively correlated with relative advantage.	Not Support
H3: Perceived risk has a negative and significant influence on the adoption of AI.	Not Support
H4: The adoption of AI is positively correlated with managerial capability.	Not Support
H5: There is a positive correlation between managerial support and AI adoption.	Support
H6: The adoption of AI and technical capability are positively correlated.	Support
H7: There is a positive correlation between data management and AI adoption.	Not Support
H8: The adoption of AI and competition’s pressure are positively correlated.	Support
H9: Vendor partnership has a positive and significant influence on the adoption of AI.	Support
H10: Market uncertainty has a positive and significant influence on the adoption of AI.	Not Support

CHAPTER 6

DISCUSSION OF RESEARCH RESULTS

The impact of AI and AI technologies on corporate enterprises is growing significantly, reshaping industries and redefining business processes. Today, many companies are either eager to implement artificial intelligence technology or are required to use it, but in both cases, they are confused about how to adapt this technology. The journey to AI adoption is fraught with challenges. To maximize AI's potential, it is necessary to gain an understanding of the mutually interdependent relationship between AI readiness and adoption, thus AI technology could be successfully adopted (Jöhnk, Weißert, & Wyrtki, 2021). Success in adopting AI requires a holistic approach considering factors affecting the adoption process. Analyzing key factors that have been identified as critical in the AI adoption process is important. To improve descriptive knowledge and to contribute AI adoption, it is essential to make in dept research on these factors that impact AI adoption (Jöhnk et al., 2021).

In this context, we sought to explore critical factors influencing the adoption of AI technologies by organizations. To address this, we formulated the following research questions: What are the key factors influencing the adoption of Artificial Intelligence technologies in organizations? How do technological, organizational and environmental factors affect AI adoption? These questions serve as a basis for exploring aspects of AI adoption. By addressing the outlined research question, this study offers a comprehensive perspective on the criteria that affect AI adoption. Results have provided us with the following outcomes explained below.

The first hypothesis in this study, which claims that compatibility influences the intention of adopting AI technology is supported. Our research findings emphasize the positive relationship and the critical role that compatibility plays in adopting AI technologies within organizations. This positive relationship is consistent with the prior research. Similar results were observed in the research of Smit, Eybers, and de Waal (2022) pointing out that enhanced compatibility and adoption go hand in hand. Companies with an existing technological framework which suitable for AI integration and technologies are more likely to experience a smoother transition to AI adoption. From a business standpoint, innovation should be compatible with the technical standards and frameworks of the organization implementing it. The smooth integration of AI with existing software and platforms helps reduce implementation challenges and increase efficiency. If AI technologies is perceived as a seamless extension of current systems, also employees are more willing to accept and engage with the technology, which reduce difficulties in the adoption process. Similarly, it has been noted in the literature that there will be less opposition to adopting AI if the solution is compatible to current technologies (Ali, Shrestha, Osmanaj, & Muhammed, 2021). In line with this, Jere & Ngidi (2020) highlighted in their study that if management and employees trust new technology's ability to align with current systems and processes, adopting it becomes easier. Therefore, if companies give importance to compatibility as selecting and implementing AI technologies, they are more likely to experience successful outcomes. Ensuring compatibility and AI technologies will continue to be a critical factor in determining the success of AI adoption.

The next hypothesis proposed that managerial support effects AI technology adoption is supported. The findings display the importance of strong managerial support as a key factor of AI adoption. The findings of this study are consistent with Chen et al. (2021) and Nguyen et al. (2022). The importance of managerial support comes from their essential role in new technology adoption. Christiansen, Haddara and Langseth (2022) also points out that support from management is considered as one of the most important organizational dimension-related elements. Managers are critical in allocating the resources and ensuring infrastructure necessary for AI adoption. They ensure integration of new systems with corporate objectives, deal with opposition to transformation, minimize user pressure and manage and inspire teams. All leaders and managers are required to inspire, manage, coordinate, and lead teams in an effective way in the adoption process, which creates a significant impact. Due to these reasons, managerial support is important, especially preparing organizations for technological changes. Our findings indicates that if there is managerial support, the possibility of adopting AI technologies may increase. In line with this, Elbanna (2013) points out that if the managers provide regular and consistent assistance throughout new technologies implementation, adoption process may easily be completed. In the end, an effective, smooth and trustworthy integration of AI is made possible by strong managerial support, thus the technology's potential to encourage innovation and add value is ensured.

Another hypothesis indicating that technical capability affects AI adoption is supported. There is a positive relation between technical capability and AI adoption. AI adoption is difficult at the organizational level without sufficient technical capability and technological innovation. It requires high technical infrastructure support. It is important to consider the nature of AI systems which calls for constant enhancement and adjustment to new developments in the industry, thus companies with strong technological expertise may stay at the cutting edge of innovation.

Furthermore, AI technologies must be generally customized to meet specific business needs which require the technological know-how to adapt them and also incorporate into current workflows and systems. In line with this, in his study, Odeibat (2023) indicates that while diminishing integration challenges, strong technical capabilities enable the information technology team to launch artificial intelligence solutions efficiently and rapidly. Schmitt et al.'s (2019) findings are also aligned with our findings by indicating that IT infrastructure and skilled personnel are important for leveraging the potential of AI technologies. Similarly, Al-Waseai and Kasım (2021) find similar results to our findings indicating positive relationship between technical capability and AI Adoption. Therefore, from a practical perspective, organizations trying to adopt AI technologies should focus on their technical capabilities. If companies reach a certain level of technical capability, they are more likely to implement the adoption process efficiently and quickly.

The upcoming hypothesis which proposes that competition's pressure affects AI technology adoption is supported. Competition pressure is an important factor in the adoption of Artificial Intelligence technologies, because companies aim to stay ahead of competitors. Due to pressure from rivals, firms speed up the implementation of new technology. Komathi and Sim (2024) point out that customer and technological trends shape organizations' decisions to adopt new digital technologies. With the adoption of new technologies by competitors, customer expectations are reshaped. Thus, to maintain a competitive edge and differentiate themselves, companies focus on new technologies and opportunities coming with them. Our research findings are in line with previous studies, which highlighted that competition's pressure increase rapid innovation of new technologies (Min & Kim, 2021; Na, Heo, Han, Shin, & Roh, 2022). Therefore, to meet consumer demands with more flexible as well as quicker services and stay competitive, organizations feel required to adopt Artificial Intelligence technologies (Gutierrez, Boukrami, & Lumsden, 2015). All in all, the positive relation between competition’s pressure and AI adoption are further supported.

The other hypothesis in this research which claims that vendor partnership has an impact on AI technology adoption is supported. The result of this research demonstrates that vendor partnership and AI technology adoption have a positive relationship. This result supports the findings of Chen et al. (2021) and Nguyen et al. (2022). As a newly emerging fields, AI is characterized by high technological challenges and complexity. Companies generally prefer contracting with specialized companies for these new high-tech solutions and services rather than building them in-house. Furthermore, compared with others, it is a rapidly developing technology, and there is a lack of skilled experts in this field. Due to the complexity of the field and lack of resources, partners' support is of great importance, especially in integration and adoption processes. Chen (2019) also points out in his research that businesses should establish networks with partners as adopting AI technologies. It could be said that vendor partnership is important for Artificial Intelligence adoption. Therefore, companies with strong relationships with their vendors will increase their probability of success in AI adoption.

For variables market uncertainty, relative advantage, managerial capability, and data management, although the analysis revealed a positive relationship with AI adoption, the results were not statistically significant. In the case of market uncertainty, this result suggests that although uncertain market conditions might increase firms' awareness for advanced tools like AI technologies, it may not directly convert into adoption. Especially in an uncertain market, firms may hesitate to invest in AI technologies because of their concerns on substantial costs, additional risks, uncertain short-term benefits and long-term results. However, AI adoption could be a response to these uncertainties like using predictive analytics to anticipate market trends and machine learning for optimizing decisions (Okeleke, Ajiga, Folorunsho, & Ezeigweneme, 2024). Furthermore, in unstable and dynamic market conditions, firms should focus on the critical role of managers. As emphasized in Wu, Song, Lu and Guo (2024) research, managers have the ability to handle risks and overcome obstacles in market as well as achieve growth, therefore they have an important role to deal with market uncertainity.

Relative advantage of AI adoption generally accepted as the benefits of AI technologies like cost efficiency, operational improvement, optimization process. However, despite these benefits, the real concerns about adoption and relative advantage could be associated with how to measure these benefits and align AI's adoption with short-term benefits and strategy. In this case, managers should consider AI as a strategic investment rather than a short-terms cost. In a similar way, Nguyen et.al.(2022) the importance of using this as a long-terms strategy. Recognizing the long-term benefits of AI is likely to speed up its implementation.

In terms of managerial capability, strong managerial skills are critical for implementing AI however these capabilities alone are not sufficient for AI adoption. To maximize the impact of managerial capability, organizations must have a wholistic approach with other critical factors like managerial support. Chen (2019) points out the importance of addressing managerial capability with a holistic approach in the adoption process. Thus, the core potential of managerial capability can be activated. Therefore, managerial capability may increase AI adoption.

In case of data management, suitable data infrastructure is necessary for AI adoption. Despite being an essential part of process, it alone is not sufficient to drive adoption. Organizations may face challenges about data like immaturity, poor resources, data literacy. Firms must focus on developing data quality, data maturity, data driven decision making and integrating advanced data analytics. Without proper alignment, data management may fail to achieve its full potential in supporting AI adoption.

In perceived risk case, we have expected to have a negative relationship with AI technology adoption in parallel to the findings in Mwemezi and Mandari (2024). However, there is not a negative relationship between variables in the results. The relationship with AI adoption and perceived risk could be more complex than we assumed. AI technologies by its nature and technological development process, have diverse risks in different categories. AI risks include ethical risks, privacy violations, societal risks, system failures, unintended consequence, fear of losing human control and job. AI technologies and perceptions are affected by the risks they include in nature (Bengio et al., 2023; Roose, 2022). Although based on the literature review, we initially expected a negative relationship, it is possible that unexpected factors or mediators could have influenced a positive relationship. Therefore it is crucial to consider that factors which are not included in the model. These factors could effect how the perceived risk is interpreted; thus played a role in shaping this positive relationship. Aligned with this argument, the research of Wilczek, Thäsler-Kordonouri and Eder (2024) can be brought into consideration. Their findings suggest that cultural dimensions, such as uncertainty avoidance, significantly shape perceptions of AI risks and AI technologies. Therefore, in the case of perceived risk, there should be more holistic approach. One of the explanations could be related to management of these perceieved risks and alternative potential outcomes. Companies should focus on how to manage these risks and their effects. They create a sense of fear and hesitation, but at the same time, they can be transformed into opportunities by using an effective management strategy. In their research, Alzaabi and Shuhaiber (2022) investigate AI adoption and perceived risk relation in United Arab Emirates. Their research revealed that while AI availability might lead to the replacement of human roles, perceived risks associated with AI could contribute to the creation of new job opportunities, positively impacting the human workforce. Another explanation for our research results may lie in the reasons like geography and sample size. The effects of these factors on AI adoption have also been measured in McElheran et al. (2024), which shows us the impact of these factors on AI adoption. Another possible explanation could be related to rapid development and prevalence of AI. Although the risks are considerable, companies are switching to AI technology. As discussed above, AI technologies could bring many important improvements for companies from cost reduction to efficiency. Like our research findings, research findings of Malik et al. (2021) indicate that perceived risks do not necessarily hinder adoption. Instead, it acts as a motivational driver for organizations that adopt new technologies as a solution. If perceived risks are managed properly, it can catalyze innovation adoption. Therefore, because it provided significant advantages, companies are eager to switch this technology and accept adoption. Furthermore, there is an impact of competition’s pressure. In our analysis, the research results supported that competition’s pressure has a positive impact on AI adoption. Therefore, there is a possibility that companies might adopt this technology in order not to fall behind competitors. Contrary to other views, Javani, Ng, Shakib Kotamjani and Ab Aziz (2023) find that higher levels of perceived risk, such as concerns about security and regulatory compliance, can motivate companies to adopt new technologies as a means to mitigate other risks like falling behind in the competition.

On the other hand, for constructs that do not get statistically significant results, it could be said that these results and the absence of statistical significance do not mean that the relationships between the variables are not meaningful or insignificant. There still could be a possibility for a meaningful connection. One possible explanation could be related to our sample size which might not provide enough statistical power to detect the correlation. The research results are consistent with existing literature, however, they cannot be evaluated as variables showing statistical significance. Artificial Intelligence is a newly developing field, and it is difficult to reach out to a large number of target groups. Additionally, the observed positive relationships align with existing theories and prior research in this area, suggesting that the effect may exist but requires further examination. Therefore, it is important why the results are positive yet not statistically significant, or why the relationship is a weak positive. There might be a variety of reasons behind each of this factor.

The results might also have been impacted by some contextual or environmental aspects. In this study, deep analysis based on industry was not made, therefore, there is no industry-specific division. The development level of AI technologies and usage frequency may vary among industries. Furthermore, there may also be different circumstances, such as market maturity, changes, and other issues specific to the industry. In line with this, Polisetty, Chakraborty, Kar, and Pahari (2024) underline differences and importance of industry-specific contexts in AI adoption patterns. This reason could directly influence research results, however, due to sample size population it was not possible to make industry-specific analysis. If the research sample had been separated based on industries, target audiences would have been too small to carry out the research.

Another important factor could be related to geography, differences in the level of country development and field experience, in relation to each other. There are significant differences among countries in their level of artificial intelligence development, Artificial Intelligence adoption rate and pervasiveness. Calvino and Fontanelli (2023) indicate that countries' AI adoption rates vary significantly due to differences in digital maturity, available skills and investment levels. McElheran et al. (2024) find similar results within United States. They indicate that there is an uneven pace of AI adoption across different industries and regions even within the U.S., emphasizing that while larger companies and certain sectors are leading the way, smaller firms and some regions still face significant hurdles. Zolas et al. (2021) supports this argument in their research. Their research revealed that there is also a remarkable variance in the application of AI across company size, industries and geographical areas, suggesting that companies may encounter and expect highly varied benefits from using AI. In their research, McElheran et al. (2024) also supports that AI's future, especially in businesses, will strictly depend on reducing the barriers between regions and companies and enabling a wide range of companies with different scales and industries access and use this technology. Therefore, the research results could be affected by geographical differences.

Company size could be another important factor because larger firms generally have the advantage of superior technological infrastructure, greater financial resources, and easier source of AI talents, which brings them a huge advantage compared to smaller companies. The outcome of Calvino and Fontanelli

(2023) research points out that AI is generally adopted early by larger companies and the ones in technology intensive businesses. Larger firms also can have more sophisticated IT systems, better data resources, and potential to make agreements with better partners, which is a crucial element for AI success. This could have an effect on the results of the research.

CHAPTER 7

CONCLUSION, LIMITATIONS AND FUTURE WORK

7.1 Conclusion

In the last ten years, many assumptions on the future of the Artificial Intelligence revolution and its effects on businesses, lifestyle and society have been made. Companies, like individuals, have been affected by these technological developments significantly and started to use many Artificial Intelligence technologies including automations tools, computer visions, and natural language processing. The adoption of AI is rapidly reshaping industries and transforming organizational processes, representing one of the most significant technological advancements of our time. While the benefits of AI, such as improved efficiency, enhanced decision-making, and innovation, are widely acknowledged, its adoption presents a unique set of challenges.

The adoption of AI technology should be understood through the interconnection of factors. It cannot be analyzed in isolation, thus successful technology transformation depends on a holistic approach, where each of these aspects supports and strengthens the others. Companies should not evaluate AI adoption as an independent project but should consider it as a part of their long term-focused goal. Based on the rapid technological development that we get in a few years and rate of diffusion across all industries, it seems that a future without artificial intelligence will not be possible. However, it is difficult to find a balance between encouraging AI technologies development and guaranteeing risks and the application process.

Through analyses we made, this research aimed to display the factors influencing the process of adopting this new technology. The research demonstrated positive and statistically significant effects of Compatibility, Managerial Support, Technical Capability, Competition's Pressure and Vendor Partnership on AI Adoption. In the case of Market Uncertainty, Relative Advantage, Managerial Capability, Data Management variables, we have found a positive relationship similar to literature, however it cannot be evaluated as statistically significant due to quantitative analysis results. It is important to note that these positive relationship patterns align with the explanations found in the literature review. The possible reasons for not getting statistically significant analysis results have been explained in the discussion chapter. Additionally, contrary to the negative relationship we hypothesized for Perceived Risk and AI Adoption, we found a positive relationship, which contrasts with the results of other studies in the literature.

The results of this research are expected to offer significant benefits to companies during their Artificial Intelligence technology adoption process.As indicated above, in the future, different studies can be conducted based on industry-specific, region-specific, with different theories, focused on a specific AI technology. As a result, we can say that Artificial Intelligence, as a newly developing field, has certain benefits. It is a strategic decision to use Artificial Intelligence technologies. However, there is a gap between theoretical concepts and real-world implementations of AI, and therefore there is a strong need to focus on AI technologies. Companies may struggle with how to apply and adopt this new technology in their businesses. Ongoing research will expand the application areas of Artificial Intelligence technologies, which result in a growing need for further studies in this field. Organizations must approach AI adoption with a clear understanding of its challenges and address them through strategic alignment, workforce preparation, and critical considerations. As emphasized, this adoption process is not merely a technological shift but a strategic transformation. Organizations that successfully integrate AI into their processes and operations will benefit from significant opportunities. Therefore, it is necessary to always keep an eye on this area, stay updated on current developments, and analyze the effect of these developments from the company side.

7.2 Limitations and future work

It is important to keep in mind the limitations of this research. This research was conducted with 131 participants having AI knowledge and experience. Artificial Intelligence has not yet reached its full maturity and is still developing. As a result, the number of professionals working in this field is quite limited compared to others. Therefore, the challenge of finding participants in this area is one of the limitations of this study. This small sample size could also impact the ability to achieve statistically significant results. Although the results indicate positive relationships between the variables and AI adoption, a larger sample would likely increase statistical power and ensure greater confidence in the generalizability of the outcomes. Therefore, with a larger sample size statistically significant results could be the outcome.

Furthermore, for this research, the majority of participants were from Turkey. However, artificial intelligence is a global field. Thus, conducting a study on a global scale would help provide a broader perspective. Since countries differ in their levels of development in artificial intelligence, a similar study conducted in another country could produce different results.

Besides these limitations, several points could be highlighted for future research. First of all, in this study, the TOE and DOI frameworks have been used. There are no key constructions or context-specific variables especially in the TOE framework. Many more factors other than what is included in the study might have a role in the dimensions of technology, organization, and environment in the TOE theory. It is not possible to conduct research with all scales, however, more research can be carried out using other constructs and analyzing how they impact AI adoption.

Secondly, it is important to note that Artificial Intelligence is a rapidly evolving technology, and its impact on our lives is continuously increasing. In such a swiftly evolving field, it is important for research to stay up-to-date and progress accordingly. Therefore, the results obtained from the scales used in this study might produce different outcomes in the future. Hence, a similar study could be conducted in the future with even the same constructs. Furthermore, the results of this research depend on participants' experiences as well as knowledge of AI applications and technology. Because AI technology is a rapidly developing field, knowledge and experience in AI technologies will be also rapidly changing. Moreover, AI technology knowledge strictly depends on the country, thus the same research can be conducted in a different country due to the high possibility of different responses.

Thirdly, there are no industrial or AI-specified technological limitations in this research due to the current development of AI technologies. However, as AI technology evolves in the future and reaches a level of maturity, it could be easier to conduct technology-specific or industry-specific research in this field. Therefore, after the increase in AI technologies level of prevalence and maturity, it would be possible to work with large sample sizes and a deeper analysis can be carried out in specific technology and industry. Thus, it will be possible to prepare and optimize industry and technology specific AI adoption strategies.

In this research the TOE and DOI theories were used. However, in the literature, there are other theories and models that can be used for acceptance and adoption of new technologies. While applying different theories on Artificial Intelligence adoption, it is possible to contribute literature by covering the identified gap. Using different theories will contribute to further comprehension of this field. In some cases, combining various theories allows for a deeper examination of complex phenomena that could not be fully explained by one theory. Therefore, we can say that using alternative theories could highlight the aspects where the theories used in this research fall short.

Moreover, using different methods like interviews and longitudinal studies can offer some benefits. It can bring a deeper understanding of the research problem and broader perspective for factors. These methods allow researchers to explore perceptions, motivations, and emerging themes, offering rich qualitative data which is very important for understanding the human and contextual elements of technology adoption. They help to get in-depth, flexible, and context-rich insights.

APPENDIX A

QUESTIONNAIRE IN ENGLISH

1)Your gender:

• Woman

• Male

• I do not want to specify

2) Your age:

• <24

• 24 - 29

• 30 - 35

• 36 - 45

• 46 - 55

• 56 - 65

• >65

3) Your Education Level:

• Primary/Middle School graduate

• High school graduate

• University student

• Graduated from a Universty

• Master's/PhD student

• Master's/PhD graduate

4) Please select the industry that the AI product/service you would consider regarding the information in this survey is adopted.

Financial Services

Technology, Media and Telecommunications

Energy, Infrastructure and Natural Resources

Retail and Consumer Products

Automotive

Industrial Production

Construction and Engineering

Health
Transportation and Logistics
Private Equity
Government Policy
Pharmaceuticals and Life Sciences
Other:

5) Please indicate the location of the organization where the Artificial intelligence product/service you will consider when answering the questions in this survey is adopted.
Country:...

6) What is the size of your company?
<100 Employees ( )
100-500 Employees ( )
500-2000 Employees ( )
>2000 Employees ( )

7) What is your current job position?
Artificial intelligence product/service user
IT Specialist (Software Developer, Analyst, Test Engineer)
Manager (Department Manager, Director and Senior Manager)
Other:

8) Please indicate how many years of work experience you have.
<3 years ( )
3-5 years ( )
5-10 years ( )
10-15 years ( )
>15 years ( )

1. Strongly Disagree 2. Disagree 3. Somewhat Disagree 4. Neither Agree nor Disagree 5. Somewhat Agree 6. Agree 7. Strongly Agree
9) AI product/service is compatible with our current communication/network environment.
10) AI product/service is compatible with our current hardware environment.
11) AI product/service is compatible with our current software environment.
12) AI product/service is compatible with our infrastructure.
13) AI product/service is compatible with computerized data resources.

14) AI product/service can increase revenues and profitability.
15) AI product/service can get higher employee productivity.
16) AI product/service can improve customer service.
17) AI product/service can better utilize IT resources.
18) AI product/service can promote flexibility and integration.
19) Adopting AI innovation lacks application maturity.
20) There has been a high cost for AI application and migration.
21) Adopting AI innovation is time consuming.
22) Inappropriate staffing and personnel shortfalls are a big issue for adopting AI innovation.
23) Our firm will not feel safe in using AI to establish strategies.
24) The fear of data safety always discourages our firm from adopting AI.
25) Overall, our firm does not have confidence and security in applying for AI.
26) The risk of cyber threats that can compromise data discourages our firm from using AI.
27) We have clear goals and objectives to adopt AI technologies innovation.
28) We have a great project management team.
29) The inter-department cooperation is very important to adopt AI technologies innovation.
30) The inter-department communication is very important to adopt AI technologies innovation.
31) Formal education and training programs can be developed to include all classes of users ranging from managers to shop floor controllers.
32) The managers explicitly demonstrate to support the adoption of AI.
33) Managers are willing to take risks involved in the adoption of AI.
34) Our managers have the ability to exploit new AI technologies before our competitors.
35) Our managers have the ability to leverage IT new technologies as a strategic core competence.
36) Our managers have a strong understanding of how AI technology can be used to increase business performance.
37) We have standardized process for IT innovation.
38) We have the ability to quickly integrate new AI technologies into our existing infrastructure.
39) Our IT strategies support our business strategies.
40) We have suitable hardware/software to protect the security and privacy of our systems and networks.
41) Our firm knows how AI technology can be used to support our operations.
42) Our firm has a good understanding of how AI technologies can be used in our business.
43) We have the necessary technical, managerial and other skills to implement AI.
44) Our business values and norms would not prevent us from adopting AI in our operations.

45) The data we currently use in our business is reliable.

46) There is an agreement on clearly defined business rules and a set of data definitions.

47) The search for and use of data/information to support decision-making is encouraged.

48) Decision-making processes involving quantitative/numerical analysis are encouraged.

49) Our firm is under pressure from competitors to adopt AI technologies.

50) Some of our competitors have already started using AI technologies.

51) Our competitors know the importance of AI and are using them for operations.

52) We have had no difficulty in obtaining assistance or reliable services from our vendors/partners.

53) Our vendors/partners are trustworthy.

54) Vendor makes decisions beneficial to my organization.

55) We have very close relationships with vendors/partners

56) Our vendors/partners are knowledgeable for AI technologies.

57) There is a trend in our principal industry to utilize more AI technologies for business development and applications.

58) AI has broad application prospects in our principal industry.

59) Only innovative technologies can help our company to provide perfect products and services to meet the growing personalized needs of consumers.

60) AI can help our company to gain competitiveness.

61) A timely AI technical implementation and application migration plan has been developed.

62) The plan has already been endorsed by managers.

63) A financial budget and a migration schedule have been approved.

64) Our customers highly accept new products and services using AI innovations.

65) We get improvement in the competitive position after adopting AI innovation.

APPENDIX B

QUESTIONNAIRE IN TURKISH

1) Cinsiyetiniz:

• Kadın
• Erkek
• Belirtmek istemiyorum

2) Yaşınız:

• <24
• 24 - 29
• 30 - 35
• 36 - 45
• 46 - 55
• 56 - 65
• >65

3) Eğitim Seviyeniz:

• İlkokul/Ortaokul mezunu
• Lise mezunu
• Üniversite öğrencisi
• Üniversite mezunu
• Yüksek lisans/Doktora öğrencisi
• Yüksek lisans/Doktora mezunu

4) Lütfen bu anketteki soruları cevaplarken göz önünde bulunduracağız Yapay Zeka ürünü/servisinin kullanıldığı kuruluşun çalışma alanını seçiniz.

Finansal Hizmetler
Teknoloji, Medya ve Telekomünikasyon
Enerji, Altyapı ve Doğal Kaynaklar
Perakende ve Tüketici Ürünleri
Otomotiv
Endüstriyel Üretim
İnşaat ve Mühendislik

Sağlık
Taşımacılık ve Lojistik
Özel Sermaye
Kamu Hizmetleri
İlaç ve Yaşam Bilimleri
Diğer:

5) Lütfen bu anketteki soruları cevaplarken göz önünde bulunduracağınız Yapay zeka ürünü/servisinin kullanıldığı kuruluşun nerede olduğunu belirtiniz.
Ülke: ...

6) Şirketinizin büyüklüğü nedir?
<100 Çalışan ( )
100-500 Çalışan ( )
500-2000 Çalışan ( )
>2000 Çalışan ( )

7) Çalıştığınız şirkette şu anki pozisyonunuz nedir?
Yapay zeka ürünü/servisi kullanıcısı
BT Uzmanı(Yazılımcı, Analist, Test Mühendisi)
Yönetici(Departman Yöneticisi, Direktör ve Üst Seviye Yönetici)
Diğer:

8) Lütfen kaç yıllık iş tecrübeniz olduğunu belirtiniz.
<3 yıl ( )
3-5 yıl ( )
5-10 yıl ( )
10-15 yıl ( )
>15 yıl ( )

1. Kesinlikle Katılmıyorum 2. Katılmıyorum 3. Pek Katılmıyorum 4. Kararsızım 5. Biraz Katılıyorum 6.Katılıyorum 7. Kesinlikle Katılıyorum
9) Yapay zeka ürünü/servisi mevcut iletişim/ağ ortamımızla uyumludur.
10) Yapay zeka ürünü/servisi mevcut donanım ortamımızla uyumludur.
11) Yapay zeka ürünü/servisi mevcut yazılım ortamımızla uyumludur.
12) Yapay zeka ürünü/servisi altyapımızla uyumludur.

13) Yapay zeka ürünü/servisi bilgisayarlı veri kaynaklarıyla uyumludur.
14) Yapay zeka ürünü/servisi gelirleri ve karlılığı artırabilir.
15) Yapay zeka ürünü/servisi daha yüksek çalışan verimliliği sağlayabilir.
16) Yapay zeka ürünü/servisi müşteri hizmetlerini iyileştirebilir.
17) Yapay zeka ürünü/servisi BT kaynaklarını daha iyi kullanabilir.
18) Yapay zeka ürünü/servisi esnekliği ve entegrasyonu destekleyebilir.
19) Yapay zeka inovasyonunu benimsemek uygulama olgunluğundan yoksundur.
20) Yapay zeka uygulaması ve geçişinin yüksek bir maliyeti oldu.
21) Yapay zeka inovasyonunu benimsemek zaman alıcıdır.
22) Uygun olmayan personel alımı ve personel eksiklikleri, yapay zeka inovasyonunun benimsenmesinde büyük bir sorundur.
23) Firmamız stratejilerini oluşturmak için yapay zekayı kullanma konusunda kendini güvende hissetmeyecektir.
24) Veri güvenliği korkusu, firmamızı her zaman yapay zekayı benimsemekten caydırır.
25) Genel olarak firmamızın yapay zekaya başvurma konusunda güveni ve güvencesi yok.
26) Verileri tehlikeye atabilecek siber tehdit riski firmamızı yapay zeka kullanmaktan caydırıyor.
27) Yapay zeka teknolojilerindeki yenilikleri benimsemek için net hedeflerimiz ve amaçlarımız var.
28) Harika bir proje yönetim ekibimiz var.
29) Yapay zeka teknolojilerindeki yeniliklerin benimsenmesi için departmanlar arası işbirliği çok önemlidir.
30) Departmanlar arası iletişim, yapay zeka teknolojilerindeki yeniliği benimsemek için çok önemlidir.
31) Örgün eğitim ve öğretim programları, yöneticilerden atölye kontrolörlerine kadar tüm kullanıcı sınıflarını kapsayacak şekilde geliştirilebilir.
32) Yöneticiler yapay zekanın benimsenmesini desteklediklerini açıkça gösteriyor.
33) Yöneticiler yapay zekanın benimsenmesiyle ilgili riskleri almaya isteklidir.
34) Yöneticilerimiz yeni yapay zeka teknolojilerinden rakiplerimizden önce istifade etme becerisine sahiptir.
35) Yöneticilerimiz, yeni BT teknolojilerinden stratejik bir temel yetkinlik olarak yararlanma becerisine sahiptir.
36) Yöneticilerimiz, iş performansını artırmak için yapay zeka teknolojisinin nasıl kullanılabileceği konusunda güçlü bir anlayışa sahiptir.
37) Bilgi Teknolojileri yenilikleri için standartlaştırılmış bir sürecimiz var.
38) Yeni yapay zeka teknolojilerini mevcut altyapımıza hızlı bir şekilde entegre etme yeteneğine sahibiz.

39) Bilgi Teknolojileri stratejilerimiz iş stratejilerimizi desteklemektedir.
40) Sistemlerimizin ve ağlarımızın güvenliğini ve gizliliğini korumak için uygun donanıma/yazılıma sahibiz.
41) Firmamız, operasyonlarımızı desteklemek için yapay zeka teknolojisinin nasıl kullanılabileceğini biliyor.
42) Firmamız yapay zeka teknolojilerinin işimizde nasıl kullanılabileceği konusunda iyi bir kavrayışa sahiptir.
43) Yapay zekayı uygulamak için gerekli teknik, yönetimsel ve diğer becerilere sahibiz.
44) İş değerlerimiz ve normlarımız, operasyonlarımızda yapay zekayı benimsememizi engellemez.
45) Şu anda işimizde kullandığımız veriler güvenilirdir.
46) Açıkça tanımlanmış iş kuralları ve bir grup veri tanımı üzerinde bir anlaşma vardır.
47) Karar almayı desteklemek için verinin/bilginin aranması ve kullanılması teşvik edilir.
48) Niceliksel/sayısal analiz içeren karar verme süreçleri teşvik edilir.
49) Firmamız rakiplerin yapay zeka teknolojilerini benimseme baskısı altındadır.
50) Rakiplerimizden bazıları zaten yapay zeka teknolojilerini kullanmaya başladı.
51) Rakiplerimiz yapay zekanın önemini biliyor ve bunları operasyonlar için kullanıyor.
52) Tedarikçilerimizden/ortaklarımızdan yardım veya güvenilir hizmet alma konusunda hiçbir zorluk yaşamadık.
53) Tedarikçilerimiz/ortaklarımız güvenilirdir.
54) Tedarikçilerimiz, kuruluşumun yararına kararlar verir.
55) Tedarikçiler/ortaklarla çok yakın ilişkilerimiz var.
56) Tedarikçilerimiz/ortaklarımız yapay zeka teknolojileri konusunda bilgilidir.
57) Ana sektörümüzde iş geliştirme ve uygulamalar için daha fazla yapay zeka teknolojisi kullanma eğilimi var.
58) Yapay zekanın ana sektörümüzde geniş uygulama olanakları var.
59) Yalnızca yenilikçi teknolojiler, tüketicilerin artan kişisel ihtiyaçlarını karşılamak için şirketimizin mükemmel ürün ve hizmetler sunmasına yardımcı olabilir.
60) Yapay zeka şirketimizin rekabet gücü kazanmasına yardımcı olabilir.
61) Yapay zeka adaptasyonu için uygun zamanda bir yapay zeka teknik uygulaması ve uygulama geçiş planı geliştirildi.
62) Bu plan halihazırda yöneticiler tarafından uygun bulundu.
63) Mali bütçe ve geçiş planı onaylandı.
64) Müşterilerimiz yapay zeka yeniliklerini kullanan yeni ürün ve hizmetleri büyük ölçüde kabul ediyor.
65) Yapay zeka yeniliğini benimsedikten sonra rekabetçi konumumuz iyileşiyor.

APPENDIX C

ETHICS COMMITTEE APPROVAL

T.C.
BOĞAZİÇİ ÜNİVERSİTESİ REKTÖRLÜĞÜ
Sosyal ve Beşeri Bilimler İnsan Araştırmaları Etik Kurulu (Sbinarek)

Sayı : E-84391427-050.04-186808 03.07.2024
Konu : 2024-51T Kayıt Numaralı Başvurunuz Hakkında

Sayın Dr. Öğr. Üyesi Nazım TAŞKIN

Tez danışmanlığını yürüttüğünüz öğrenciniz Dilek Çabuk'un "Yapay Zeka Adaptasyonunu Etkileyen Başarı Faktörleri" başlıklı projesi ile Boğaziçi Üniversitesi Sosyal ve Beşeri Bilimler İnsan Araştırmaları Etik Kurulu (SBİNAREK)'e yaptığınız 2024-51T kayıt numaralı başvuru 28.06.2024 tarih ve 2024/05 sayılı kurul toplantısında incelenmiş ve projeye etik onay verilmesi uygun bulunmuştur.

Bu karar tüm üyelerin toplantıya on-line olarak katılımıyla ve oybirliği ile alınmıştır. Onay mektubu tüm üyeler adına Komisyon Başkanı tarafından e-imzalanmıştır. Bilgilerinizi rica ederiz.

Saygılarımızla,

Dr. Öğr. Üyesi Işıl ERDUYAN
Kurul Başkanı

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Mühendis
Telefon No:

APPENDIX D

DESCRIPTION OF CONSTRUCTS AND ITEMS

Construct	Question	Source
Compatibility (COMP)		
CMPT1	AI product/output is compatible with our current communication/network environment.	(Chen et al.,2021)
CMPT2	AI product/output is compatible with our current hardware environment.	
CMPT3	AI product/output is compatible with our current software environment.	
CMPT4	AI product/output is compatible with our infrastructure.	
CMPT5	AI product/output is compatible with computerized data resources.	
Relative Advantage (RADV)		
RADV1	AI product/output can increase revenues and profitability	(Chen et al.,2021)
RADV2	AI product/output can get higher employee productivity.	
RADV3	AI product/output can improve customer service.	
RADV4	AI product/output can better utilize IT resources.	
RADV5	AI product/output can promote flexibility and integration.	
Complexity (COMP) (Deleted)		
COMP1	Adopting AI innovation lacks application maturity. (Deleted)	(Chen et al.,2021)
COMP2	There has been a high cost for AI application and migration. (Deleted)	
COMP3	Adopting AI innovation is time consuming. (Deleted)	
COMP4	Inappropriate staffing and personnel shortfalls are a big issue for adopting AI innovation. (Deleted)	
Managerial Capability (MCAP)		
MCAP1	We have clear goals and objectives to adopt AI technologies innovation. (Deleted)	(Chen et al.,2021)
MCAP2	We have great project management team. (Deleted)	
MCAP3	The inter-department cooperation is very important to adopt AI technologies innovation.	
MCAP4	The inter-department communication is very important to adopt AI technologies innovation.	
MCAP5	Formal education and training programs can be developed to include all classes of users ranging from managers to shop floor controllers. (Deleted)	
Managerial Support (MSUP)		
MSUP1	The managers explicitly demonstrate to support the adoption of AI. (Deleted)	(Chen et al.,2021)
MSUP2	Managers are willing to take risks involved in the adoption of AI. (Deleted)	
MSUP3	Our managers have the ability to exploit new AI technologies before our competitors.	
MSUP4	Our managers have the ability to leverage IT new technologies as a strategic core competence	

MSUP5	Our managers have a strong understanding of how AI technology can be used to increase business performance.	
Technical Capability (TECC)		
TECC1	We have standardized process for IT innovation.	(Chen et al.,2021)
TECC2	We have the ability to quickly integrate new AI technologies into our existing infrastructure.	
TECC3	Our IT strategies support our business strategies.	
TECC4	We have suitable hardware/software to protect the security and privacy of our systems and networks.	
Organizational Readiness (ORGR) (Deleted)		
ORGR1	Our firm knows how AI technology can be used to support our operations (Deleted)	(Ifinedo, 2011)
ORGR2	Our firm has a good understanding of how AI technologies can be used in our business. (Deleted)	
ORGR3	We have the necessary technical, managerial and other skills to implement AI. (Deleted)	
ORGR4	Our business values and norms would not prevent us from adopting AI in our operations. (Deleted)	
Data Management (DATA)		
DATA1	The data we currently use in our business is reliable.	(Stjepić et al., 2021)
DATA2	There is an agreement on clearly defined business rules and a set of data definitions.	
DATA3	The search for and use of data/information to support decision-making is encouraged.	
DATA4	Decision-making processes involving quantitative/numerical analysis are encouraged	
Competition's Pressure (CP)		
CP1	Our firm is under pressure from competitors to adopt AI technologies	(Ifinedo, 2011)
CP2	Some of our competitors have already started using AI technologies.	
CP3	Our competitors know the importance of AI and are using them for operations.	
Vendor Partnership (VENP)		
VENP1	We have had no difficulty in obtaining assistance or reliable services from our vendors/partners.	(Chen et al.,2021)
VENP2	Our vendors/partners are trustworthy.	
VENP3	Vendor makes decisions beneficial to my organization.	
VENP4	We have very close relationships with vendors/partners	
VENP5	Our vendors/partners are knowledgeable for AI technologies.	
Market Uncertainty (MUNC)		
MUNC1	There is a trend in our principal industry to utilize more AI technologies for business development and applications. (Deleted)	(Chen et al.,2021)
MUNC2	AI has broad application prospects in our principal industry	
MUNC3	Only innovative technologies can help our company to provide perfect products and services to meet the growing personalized needs of consumers. (Deleted)	
MUNC4	AI can help our company to gain competitiveness.	
Perceived Risks (PR)		
PR1	Our firm will not feel safe in using AI to establish technology strategies.	(Mwemezi & Mandari, 2024)
PR2	The fear of data safety always discourages our firm from adopting AI.	

PR3	Overall, our firm does not have confidence and security in applying for AI.	
PR4	The risk of cyber threats that can compromise data discourages our firm from using AI	
AI Adoption (ADOP)		
ADOP1	A timely AI technical implementation and application migration plan has been developed	(Chen et al.,2021)
ADOP2	The plan has already been endorsed by managers.	
ADOP3	A financial budget and a migration schedule have been approved.	
ADOP4	Our customers highly accept new products and services using AI innovations. (Deleted)	
ADOP5	We get improvement in the competitive position after adopting AI innovation. (Deleted)	

APPENDIX E

ITEMS AND DESCRIPTIVE STATISTICS

Factors	CMPT	RADV	PR	MCAP	TECC	MSUP	MUNC	DATA	CP	VENP	ADOP
CMPT1	0.886	-0.118	0.091	0.010	-0.259	0.112	0.160	0.039	0.021	-0.074	0.059
CMPT2	0.923	-0.017	0.014	-0.105	0.085	-0.096	-0.024	-0.071	0.001	0.130	-0.004
CMPT3	0.943	-0.005	0.045	0.025	-0.020	0.017	-0.083	0.119	0.054	-0.039	0.044
CMPT4	0.955	0.062	-0.105	0.029	0.007	-0.039	-0.114	0.075	-0.050	0.012	-0.030
CMPT5	0.892	0.073	-0.040	0.042	0.184	0.012	0.076	-0.172	-0.025	-0.033	-0.069
RADV1	-0.080	0.880	-0.031	-0.110	0.079	0.119	0.280	-0.118	0.025	0.017	-0.105
RADV2	-0.107	0.760	-0.139	-0.018	0.366	-0.400	-0.306	-0.064	-0.032	0.030	0.192
RADV3	0.032	0.863	0.023	0.033	-0.057	0.070	0.132	-0.041	-0.272	0.102	0.030
RADV4	-0.073	0.896	0.150	0.019	0.061	0.020	-0.104	0.073	0.164	-0.016	-0.023
RADV5	0.235	0.805	-0.026	0.081	-0.439	0.150	-0.043	0.152	0.113	-0.138	-0.073
PR1	0.029	-0.070	0.870	0.055	-0.031	-0.112	0.025	0.036	0.054	-0.066	-0.011
PR2	0.001	-0.050	0.902	-0.008	0.180	0.002	0.169	-0.103	-0.005	0.021	-0.083
PR3	0.049	0.056	0.900	-0.127	-0.019	0.139	-0.006	0.000	0.021	0.025	-0.157
PR4	-0.080	0.063	0.882	0.084	-0.135	-0.034	-0.191	0.070	-0.069	0.019	0.255
MCAP3	-0.044	-0.009	0.029	0.944	0.033	0.003	-0.021	0.014	-0.057	-0.020	0.037
MCAP4	0.044	0.009	-0.029	0.944	-0.033	-0.003	0.021	-0.014	0.057	0.020	-0.037
TECC1	-0.111	0.037	0.053	0.115	0.852	-0.205	-0.040	0.019	-0.094	-0.018	0.297
TECC2	-0.020	-0.086	-0.004	-0.042	0.817	0.318	0.230	0.106	-0.052	-0.246	-0.075
TECC3	-0.052	0.011	-0.010	0.071	0.871	0.054	-0.065	-0.105	0.022	-0.055	-0.080
TECC4	0.206	0.039	-0.045	-0.166	0.758	-0.174	-0.129	-0.015	0.137	0.348	-0.161
MSUP3	0.081	0.005	-0.025	-0.006	-0.089	0.942	0.019	-0.045	0.009	0.018	-0.073
MSUP4	0.009	-0.071	0.061	-0.021	-0.001	0.951	0.113	0.064	-0.041	-0.034	0.042
MSUP5	-0.090	0.066	-0.036	0.028	0.089	0.943	-0.132	-0.020	0.032	0.016	0.031
MUNC2	-0.047	-0.233	0.085	0.130	-0.134	-0.000	0.887	0.019	0.082	-0.074	0.237
MUNC4	0.047	0.233	-0.085	-0.130	0.134	0.000	0.887	-0.019	-0.082	0.074	-0.237
DATA1	0.015	0.120	0.170	-0.197	0.130	-0.093	0.043	0.835	-0.059	0.131	-0.023
DATA2	-0.023	-0.146	-0.051	-0.146	-0.181	0.201	0.028	0.792	-0.007	0.084	0.015

DATA3	-0.039	0.069	-0.044	0.089	0.179	0.031	-0.014	0.866	0.109	-0.116	-0.127
DATA4	0.046	-0.051	-0.074	0.237	-0.140	-0.127	-0.054	0.856	-0.046	-0.088	0.137
CP1	0.109	0.155	0.088	-0.055	0.005	-0.062	-0.216	0.119	0.798	-0.098	0.221
CP2	-0.066	-0.075	-0.109	0.072	0.034	-0.077	0.132	-0.125	0.914	0.036	-0.052
CP3	-0.030	-0.063	0.035	-0.025	-0.041	0.137	0.059	0.022	0.874	0.052	-0.147
VENP1	-0.100	0.115	0.004	-0.177	0.174	0.102	-0.050	-0.017	0.044	0.766	-0.079
VENP2	0.061	-0.146	-0.028	0.069	-0.007	-0.219	-0.014	0.042	-0.050	0.904	0.035
VENP3	0.025	0.140	-0.101	0.170	-0.038	-0.071	-0.157	0.022	-0.015	0.871	-0.071
VENP4	-0.036	-0.082	0.051	0.009	-0.043	-0.044	-0.015	0.072	0.047	0.857	0.052
VENP5	0.038	-0.010	0.084	-0.105	-0.073	0.279	0.256	-0.135	-0.020	0.787	0.058
ADOP1	0.009	-0.008	0.073	-0.003	-0.114	0.076	0.102	0.060	-0.050	-0.035	0.959
ADOP2	0.017	-0.037	-0.041	0.062	0.163	-0.055	0.011	-0.107	0.032	0.002	0.965
ADOP3	-0.026	0.046	-0.032	-0.059	-0.051	-0.021	-0.113	0.048	0.018	0.033	0.953

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