THE CRITICAL FACTORS IMPACTING ARTIFICIAL INTELLIGENCE APPLICATIONS ADOPTION IN KENYA.

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A RESEARCH PROJECT SUBMITTED TO THE SCHOOL OF COMPUTING AND INFORMATICS IN PARTIAL FULFILLMENT OF THE REQUIREMENTS FOR THE AWARD OF THE DEGREE OF BACHELOR OF SCIENCE IN COMPUTER SCIENCE OF GRETSA UNIVERSITY.

NOVEMBER, 2023

STUDENT DECLARATION PAGE

STUDENT DECLARATION PAGE

This Proposal is my original work and has not been presented for award of a degree or for any similar purpose in any other institution.

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This proposal has been submitted with my approval as university supervisor.

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ABSTRACT

The concept of changing electronic devices into intelligent beings with human-like cognitive capacities is referred to as artificial intelligence (AI). Aspects of human intelligence, such as learning, reasoning, problem solving, voice recognition, and planning, can be simulated by computer systems. AI applications are being developed to assist businesses and entrepreneurs in making decisions. The purpose of this research is to look into the prevalence of artificial intelligence applications at the organisational level in Kenya. The key notion of the technological-organizational environment is used in this theoretical model, which is based on how technological and environmental elements influence organisational decisions to adopt technological innovations (TOE). The study collected data from 193 senior executives responsible for information systems in private and public firms to evaluate the model, which is influenced by ten major factors. The data was examined using structural equation modelling (SEM). The findings show that technological compatibility, comparative advantage, technical complexity, technical capabilities, management capabilities, organisational readiness, government involvement, market uncertainty, and supplier partnerships all have a significant impact on the adoption of AI applications. Surprisingly, the study discovered no statistically significant link between firm size and AI usage. As a result, AI application implementation can help advance current research on TOE AI implementation.

CHAPTER ONE: INTRODUCTION

1.1 Background to the Study

Software and systems engineers are developing new ways to increase profits, reduce costs, and improve organizational performance in response to the rise of artificial intelligence (AI). Davenport and Ronanki (2018) note that the competitive landscape of industries is now heavily influenced by AI. According to Alsheibani et al. (2018), AI is a set of tools and technologies that can improve organizational performance by creating intelligent systems that can solve complex problems by mimicking human intelligence. This information is crucial for strategic planning and has been used by companies to outperform their competitors (Variant, 2018).Lancebotham et al. (2017) suggest that AI should have a positive impacts on society, such as human enhancement, which should be considered when discussing economic growth. AI is already being implemented and used at government, industry and private level, and the Kenyan government has clear plans to implement AI in the public sector by 2030. This initiative is gaining momentum at across Africa, highlighting the importance for government organizations to lead and launch AI projects in their communities to meet their business needs.

Artificial intelligence is the imitation of various human intelligence processes by computers, especially computer systems (Agrawal et al., 2019).Alsheibani et al. (2018) define artificial intelligence as the development of intelligent artificial systems capable of mimicking human thought processes. Computer systems can replicate a range of human intelligence capabilities, including speech recognition, learning, problem solving, and decision making. With artificial intelligence, cognitive automation is now possible, going beyond the realms of robot games and knowledge representation (Dwivedi et al.Artificial intelligence is considered the most important strategic technology for businesses, with the potential to increase productivity and improve customer experience (Elliot & Andrews, 2017; Varian, 2018; Brynjolfsson & McAfee, 2017) . Large companies such as Google, Amazon, IBM and Apple have already adopted AI (Nguyen & Tran, 2019). According to Dobberstein and Chua (2021), automation and artificial intelligence are expected to add $120 million to Kenya's GDP by 2030. Soon, however, Ghee Chua and Dobberstein (2021) found that only 6% of firms Kenyan companies regularly invested in AI and automation, compared to more than 25% of companies outside the country.

This study investigates the impact of technical, organisational, and environmental factors on the adoption of AI applications. Data from Kenyan mid-level AI professionals, IT managers, IT leaders (CIO, CEO), and IT personnel will be used to evaluate research models and hypothetical linkages. The results obtained from this investigation will also contribute to empirical research on contextual factors impacting AI application adopters' decision-making utilising huge datasets rather than specific situations. Furthermore, the findings of this study should assist AI application practitioners and project managers in developing policies that are matched with relevant contextual elements to promote the effective adoption of AI applications in current and future businesses.

1.2 Statement of Research Problem

Artificial intelligence technology has the potential to revolutionize various industries and enhance economic growth and development in Kenya. However, despite the growing interest in AI, there is limited adoption of AI applications in the country. To promote the uptake of AI technology, it is essential to understand the critical factors that impact its adoption.

The factors that impact AI adoption can be both external and internal to organizations. External factors may include regulatory and legal frameworks, the availability of infrastructure and technology, and cultural and societal attitudes towards AI. Internal factors may include the organization's size, financial resources, technological capabilities, and human resources.

This study aims to identify the critical factors that impact AI adoption in Kenya and provide insights into how these factors can be addressed. By analyzing both internal and external factors, the study will provide a comprehensive understanding of the barriers and facilitators to AI adoption in Kenya. The research will also examine the extent to which these factors impact AI adoption in the country.

The study's findings will have significant implications for policymakers, organizations, and other stakeholders involved in promoting the adoption of AI technology in Kenya. The insights gained from this research will inform the development of strategies and policies that address the critical factors that impact AI adoption. Ultimately, this research will contribute to enhancing the understanding of AI adoption in Kenya and promoting the uptake of this technology in the country.

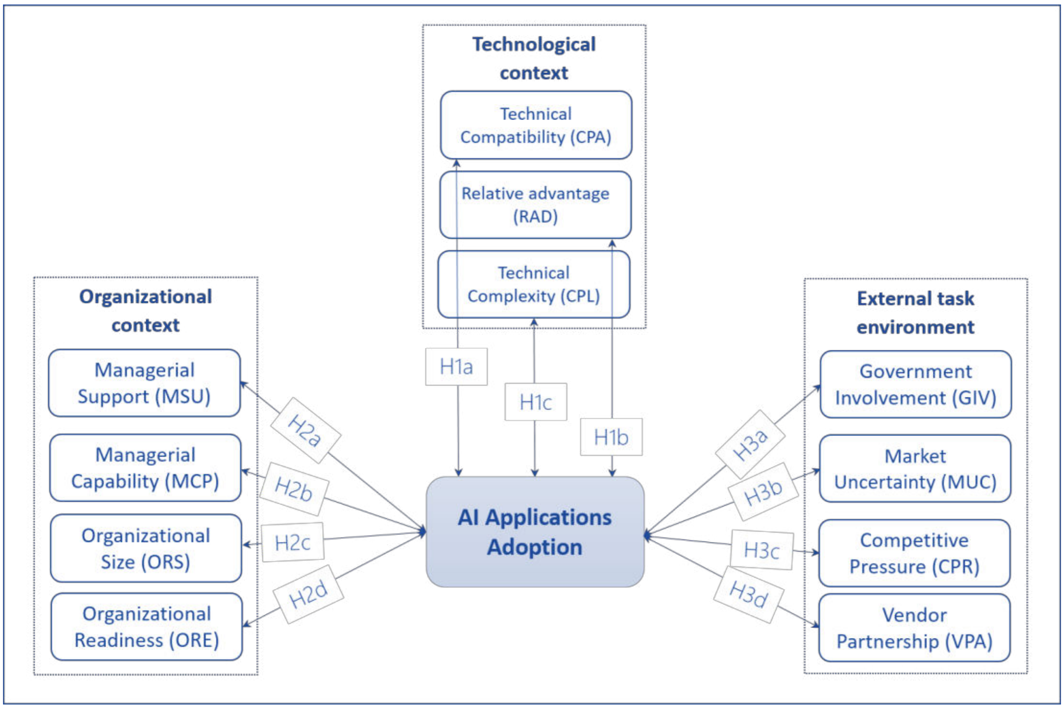
1.3 Purpose of Study

The purpose of this research was to look into the effects of technological, organisational, and environmental settings on the adoption of AI applications in Kenya.

1.4 Conceptual Framework

Based on artificial intelligence, this study divides success criteria into three categories: technology context, organisational context, and external environment. Figure 1 depicts the AI-related technological characteristics category, which includes components such as compatibility, relative advantage, and complexity. Management support, organisational scale, managerial ability, and organisational readiness are all variables in the organisational context category. Government intervention, market instability, competitive hurdles, and supplier alliances are examples of external environment factors. This section offers a modified technology acceptance model framework to identify the research challenge and create a research model.

Figure 1



1.4.1 Technological Context

Several studies have investigated the impact of innovative traits on the invention process from a technological standpoint. Kwon and Zmud (1997) and Chau and Tam (1987) are among the researchers who have explored this area. DOI theory by Rogers (1995) outlines five innovation traits, including compatibility, relative advantage, complexity, testability, and observability, but only the first three have been consistently associated with organizational-level innovation adoption. This finding is supported by studies conducted by Tornatzky and colleagues (1990) and Wu et al. (2007). Therefore, technology plays a crucial role in highlighting the critical components of AI decision-making.

Technical Compatibility: According to various studies, technical compatibility is an essential factor in the adoption of innovation (Chong & Bauer, 2000; Dedrick & West, 2004; Oliveira et al., 2010; Azadegan & Teich, 2010; Oliveira et al., 2014). It refers to the ability of an innovation to provide value and meet the needs of potential customers while being compatible with existing technology. High-level interoperability can facilitate adoption, particularly in the case of artificial intelligence (Ding et al., 2015). Machine learning, in particular, requires vast amounts of data. If AI technology is compatible with existing IT settings, it can be installed more efficiently and cost-effectively, thereby increasing its acceptance. Rogers (1995) emphasizes that compatibility is one of the five key innovation traits in DOI theory.

Relative Advantage: Innovation's relative advantage refers to the extent to which it is perceived to be better than the existing strategy it replaces (Yang et al., 2013). The perceived value of innovation is a significant factor that affects the organization's willingness to adopt new technology (Plessis & Smuts, 2021). New technologies that offer clear benefits in terms of operational and strategic efficiency are more likely to be adopted (Greenhalgh et al., 2004). In recent years, AI has been implemented in automated network operations, customer-facing voice and speech services, and chatbots for customer support (Elkhatib et al., 2019). Such applications of AI assist companies in reducing operational costs, enhancing customer satisfaction, improving efficiency, and providing superior services.

Technical Complexity: According to Yang et al (2013), the technical complexity of an innovation refers to the level of difficulty in understanding and applying it. AI is considered difficult due to factors such as its immaturity, high cost, lengthy development times, and the lack of IT specialists and technological expertise. Attewell (1992) states that companies tend to adopt difficult technologies only after they have developed the necessary technical know-how to effectively use and manage them. Despite the potential benefits of AI, many organizations are still in the process of learning about its applications and may not have a clear understanding of its relevance.

1.4.2 Organizational Context

Organizational competencies that influence the adoption of innovation encompass leadership, management, and managerial support tools. These competencies are inherent to an organization, specific to the organization, and not transferrable. The resource-based view (RBV) theory can help identify the organizational competencies that affect the adoption of AI. RBV theory posits that companies can gain a competitive advantage by integrating resources that are commercially valuable, difficult to replicate, and non-transferrable. Garrison and colleagues (2015) asserted this view.

Management support: Management support is considered a critical factor for successful adoption of significant organizational changes, as it plays a key role in driving resource allocation and service integration (Co et al., 1998). Various studies have identified managerial support as an essential element for information technology adoption and information system development (Kim et al., 2015; Mller & Jugdev, 2012; Nah et al., 2001; Sanders & Courtney, 1985; Teo et al., 2006). In fact, Elbanna (2013) suggests that without consistent and ongoing management assistance during the project implementation phase, there is a risk of project failure.

Managerial Capability: According to House and colleagues (2002), management talent refers to a manager's ability to persuade, inspire, and enable employees to contribute to an organization's effectiveness and success. It encompasses decision-making, fostering a positive workplace culture, achieving goals and objectives, and promoting creativity and innovation. In the information technology industry, project management, training, and ongoing education are all essential components of management competence. Businesses with strong managerial capabilities can overcome challenges and swiftly implement new technologies. By quickly deploying AI technologies, such businesses can enhance performance and gain a competitive edge.

Organizational size: Lin and Lin (2008) suggested that an organization's size plays a significant role in its ability to adopt new ideas. This is supported by several studies that indicate larger businesses tend to invest more quickly and aggressively in AI than in other types of investments. Therefore, the organizational context, which directly affects AI adoption, can be linked to the size of the organization.

Organizational Readiness: Organizational readiness is a crucial factor in the deployment of AI. According to a survey conducted by Story Science, 59% of businesses proficient in using big data also use AI technologies (Assael, 1995). As noted earlier, both the technical readiness of the organization and the skills of its staff play a significant role in AI adoption. Therefore, we believe that the availability of AI knowledge, the data necessary for training employees to use AI, and technical expertise will drive the adoption of AI.

1.4.3 Environmental Context

According to Hutajulu et al. (2021), Scott's (2008) institutional theory highlights the importance of institutional environments in shaping organizational structures and behaviors. This means that organizational decisions are not only influenced by rational efficiency goals but also social, cultural, and legitimacy considerations. External factors such as government regulations, competition, and customer expectations can encourage or discourage companies from adopting new technologies. As Kraemer and Gibbs (2004) suggest, external isomorphic pressures may push businesses towards adopting and utilizing AI.

Government Participation: According to Wang (2022), government engagement is necessary to promote IT innovation. The government should establish supportive strategies and policies to encourage the commercialization of new technology and develop new regulations. Al-Hawamdeh and Alshaer (2022) suggest that the government's framework is critical because adopting new technology is a complex process.

Uncertainty in the market: According to Hao et al. (2018), market factors such as product demand, market competition, and consumer loyalty can significantly affect business performance. Even though AI applications are still in the early stages and there is a shortage of qualified professionals and technical experts, AI has shown significant potential and can provide businesses with competitive advantages. However, complex tasks like fact recognition and fingerprint identification are better suited for AI programs.

Competitive Pressure: According to Dutton and Lippert (2006), competitive pressure stimulates technological innovation. It is often a strategic necessity for companies to adopt new technology in order to compete in the market. Porter and Millar (1985) argue that the competitive advantage of companies is temporary rather than permanent, and that advances in IT have the ability to transform the competitive environment, change the rules of the game, and alter the structure of an industry. Therefore, if businesses are able to effectively implement advanced AI applications to enhance their products and services, they can gain a competitive advantage over their competitors.

Partnering with vendors: Assael (1995) suggests that the involvement of vendors can significantly affect the speed of adoption and diffusion of new products. Vendors require large amounts of data to train their AI systems, often including sensitive consumer data. This may prevent vendors from fully marketing AI products and instead require them to work closely with their clients, businesses, to offer AI training and support during and after implementation. Collaborations between vendors and businesses can greatly impact the adoption of AI, and successful collaborations can lead to effective marketing of AI software.

1.5 Research Questions

i. From a technological standpoint, what are the essential elements of decision-making in AI?

ii. How do leadership, management, and supportive tools for managers contribute to the promotion of innovation adoption as part of organizational skills?

iii. To what extent do institutional environments influence the definition of organizational structures and behaviours?

1.6 Objectives of the study

1.6.1 General Objective

The present study sought to examine how the adoption of AI applications in Kenya is influenced by technological, organizational, and environmental contexts.

1.6.2 Specific Objectives

i. The aim of the current study was to investigate the significant and positive correlation between technical compatibility and the adoption of AI applications.

ii. The objective of the present study was to examine the significant and positive relationship between relative advantage and the adoption of AI applications.

iii. The primary goal of this study was to investigate the significant and negative correlation between technical complexity and the adoption of AI applications.

iv. This study aimed to explore the significant and positive relationship between managerial support and the adoption of AI applications.

v. The purpose of the study was to investigate the significant and positive relationship between managerial capabilities and the adoption of AI applications.

vi. The objective of this study was to investigate the significant and positive relationship between organizational size and the adoption of AI applications.

vii. This study aimed to examine the significant and positive relationship between organizational readiness and the adoption of AI applications.

viii. The aim of this study was to investigate the significant and positive relationship between government involvement and the adoption of AI applications.

ix. The purpose of this study was to explore the significant and positive relationship between market uncertainty and the adoption of AI applications.

x. This study aimed to investigate the significant and positive relationship between competitive pressure and the adoption of AI applications.

xi. The objective of the study was to examine the significant and positive relationship between vendor partnership and the adoption of AI applications.

1.7 Hypotheses of the Study

H0a: There is no significant relationship between technical compatibility and the adoption of AI applications.

H0b: There is no significant relationship between relative advantage and the adoption of AI applications.

H0c: There is no significant negative relationship between technical complexity and the adoption of AI applications.

H0d: There is no significant relationship between managerial support and the adoption of AI applications.

H0e: There is no significant positive relationship between managerial capabilities and the adoption of AI applications.

H0f: There is no significant relationship between organizational size and the adoption of AI applications.

H0g: There is no significant and positive relationship between organizational readiness and the adoption of AI applications.

H0h: There is no significant relationship between government involvement and the adoption of AI applications.

H0i: There is no significant relationship between market uncertainty and the adoption of AI applications.

H0j: There is no significant and positive relationship between competitive pressure and the adoption of AI applications.

H0k: There is no significant and positive relationship between vendor partnership and the adoption of AI applications.

1.8 Significance of Study

i. The study's findings will provide insights into the critical factors that impact AI adoption in Kenya, thereby informing policymakers and regulators about the current state of AI adoption in the country. Policymakers can use these insights to develop policies and regulatory frameworks that encourage the uptake of AI technology in Kenya, leading to economic growth and development.

ii. The research will provide organizations with a better understanding of the barriers and facilitators to AI adoption in Kenya. This will help them to make informed decisions on AI implementation, including selecting suitable AI technologies, developing appropriate training programs, and managing resources to maximize AI adoption benefits.

iii. The research will provide insights into the impact of AI adoption on the Kenyan workforce. By identifying the skills needed for AI implementation, the study will inform the development of training programs that can enhance the employability of the Kenyan workforce.

iv. The study's findings will provide insights into the cultural and societal attitudes towards AI in Kenya. Understanding these attitudes will help organizations and policymakers develop appropriate strategies for promoting AI adoption that consider local cultural and societal values.

v. The research will contribute to the body of knowledge on AI adoption, particularly in the context of developing countries like Kenya. The study's findings will provide valuable insights into the critical factors that impact AI adoption, which can inform future research in this area.

This research on the critical factors impacting AI adoption in Kenya will have significant implications for policymakers, organizations, the workforce, and the wider research community. It will provide valuable insights into the current state of AI adoption in Kenya and inform the development of strategies and policies that promote the uptake of this technology in the country.

1.9 Limitations of Study

i. Limited sample size: The study may have a limited sample size due to time and resource constraints. This limitation may affect the generalizability of the study's findings to the broader Kenyan population.

ii. Bias in participant selection: The study may be susceptible to bias in participant selection. For example, participants may be more likely to participate if they have a positive view of AI adoption, which may skew the study's findings.

iii. Limited access to data: The study may have limited access to data on AI adoption in Kenya, particularly in non-public sectors such as government or private organizations. This limitation may affect the depth and comprehensiveness of the study's analysis.

iv. Social desirability bias: Participants may provide socially desirable responses, leading to a bias in the study's findings. For example, participants may overstate their organization's commitment to AI adoption or underreport the barriers to adoption.

v. Limited scope: The study's scope is limited to Kenya, which may limit the generalizability of the findings to other developing countries with similar socio-economic conditions.

vi. Lack of historical data: Since AI adoption is a relatively new phenomenon in Kenya, there may be a lack of historical data on the topic. This limitation may affect the study's ability to provide a comprehensive analysis of the factors impacting AI adoption.

1.11 Delimitations or Scope of the Study

The study's scope will be limited to Kenya and will focus on the factors that impact AI adoption in the country. The research will involve a combination of qualitative and quantitative research methods, including surveys, interviews, and data analysis. The study will use a purposive sampling technique to select participants from different organizations and sectors in Kenya, including government, private, and non-profit organizations. The study will also review relevant literature on AI adoption in developing countries, including Kenya, to provide a comprehensive understanding of the research problem.

CHAPTER TWO: LITERATURE REVIEW

2.1 Introduction

Artificial Intelligence (AI) has emerged as one of the most transformative technologies of the 21st century, with the potential to revolutionize numerous industries and domains. While the adoption of AI has been relatively slow in many parts of the world, some regions have been early adopters of this technology, including Kenya. Kenya is one of the countries in Africa that has shown a keen interest in embracing AI applications, particularly in the telecommunication sector, banking, and healthcare.

However, despite the growing interest in AI in Kenya, there remain significant challenges and barriers to its adoption. Understanding the critical factors that impact the adoption of AI in Kenya is crucial to identifying strategies and solutions to overcome these barriers. This literature review aims to examine the existing literature on the critical factors impacting AI adoption in Kenya, including technical, organizational, and environmental factors. The review will synthesize and analyze the available evidence to identify gaps and opportunities for further research and provide recommendations for policymakers, practitioners, and researchers.

The following sections will provide an overview of the existing literature on the factors influencing AI adoption in Kenya, including an analysis of the current state of research in this field. Additionally, the review will explore the theoretical frameworks that can help to guide future research on this topic, such as the Technology-Organization-Environment (TOE) framework and the Unified Theory of Acceptance and Use of Technology (UTAUT) model. Finally, the review will discuss the implications of the findings for policymakers, practitioners, and researchers, as well as highlight the limitations of the current literature and potential directions for future research.

2.2 Technology Adoption Perspective

Modern technology has been shown to be an effective means of promoting business growth. Previous studies have focused on the implementation of new information technology (IT) and systems at both corporate and individual levels (Alsheibani et al., 2018; Oliveira et al., 2019). The Theory of Reasoned Action (TRA), developed by Ajzen (2012), provides insights into how individuals' behavior towards technological adoption is influenced by their attitudes and norms. The Technology Acceptance Model (TAM), which was based on TRA and developed by Davis (1985), aims to identify the factors that influence users' decisions on when and how to use new technologies. TAM has been validated by studies demonstrating a correlation between users' behavioral intentions and actual system usage (Lu et al., 2003).

However, TAM does not account for qualitative components or the societal impact of an information system. To address these limitations, Venkatesh et al. (2016) proposed the Unified Theory of Acceptance and Use of Technology (UTAUT), which explains users' intentions to use an information system and their subsequent usage behavior. In addition, many studies have examined the factors affecting individual-level adoption of specific technologies or systems, such as Web 2.0 technologies (McCarthy & Hayes, 1981; Lumsden & Gutierrez, 2013; Picoto, 2014). Tornatzky et al. (1990) proposed the Technology-Organization-Environment (TOE) paradigm to explain how technical and environmental factors influence organizations' decisions to adopt technological breakthroughs. This paradigm has prompted researchers to examine factors affecting organizations' adoption of IT, including the Quality Function Deployment (QFD) adoption survey conducted by Cristiano et al. (2001) and the qualitative field study on knowledge management systems (KMS) adoption and spread conducted by Quaddus and Xu (2005).

2.3 The Contexts of AI Adoption

Various theories have been employed in the study of AI adoption, including TAM, TPB, and UTAUT, but they may not be applicable to all types of research. At the organizational level, the DOI and the TOE framework are commonly used in IT implementation studies. The DOI theory, introduced by Rogers (1995), describes how an innovation spreads over time within a social system, and highlights the importance of innovation acceptance for its sustainability. Rogers categorized adopters into innovators, early adopters, early majority, late majority, and latecomers based on their traits. To encourage creativity, different approaches should be used for different user groups.

Currently, there are several studies investigating the application of AI in specific fields and its theoretical foundations, as well as its adoption at the organizational level. However, there is a lack of empirical evaluation on the acceptability of AI, and further research is required to examine the factors influencing an organization's inclination to adopt AI and its unique organizational capabilities and external environment. Alsheibani et al. (2018) presented a study framework for AI adoption, but it has not been validated for a sample of businesses, lacks empirical confirmation and hypothesis testing, and cannot expand on existing ideas due to the pervasiveness of AI and the scarcity of research on its organizational-level adoption.

The TOE framework is a suitable starting point for studying AI adoption, as it emphasizes the specific context in which the adoption process takes place and assesses the factors that can influence AI adoption. Therefore, the TOE framework serves as the theoretical foundation for this investigation, and the study methodology for AI adoption is based on Oliveira and Martins' (2011) approach. The TOE framework comprises the technology context, organizational context, and environmental context.

2.4 Theoretical Frameworks

This researched was based on the following theories:

i. TOE Framework

The proposed study on AI adoption in organizations will utilize the TOE framework as its theoretical foundation. This framework will enable the study to evaluate the technology context, organizational context, and environmental context of organizations that are contemplating the adoption of AI. Such an approach will facilitate the identification of the factors that affect AI adoption and their interconnectedness.

For instance, the technology context involves the characteristics of AI, such as its complexity and compatibility with existing systems, which can affect adoption decisions. The organizational context encompasses factors such as the organization's size, structure, culture, and resources, which can influence its readiness and capacity for AI adoption. The environmental context considers external factors such as market competition, regulations, and societal attitudes towards AI, which can affect the organization's perception of the benefits and risks of AI adoption. By using the TOE framework, the proposed study can provide a comprehensive analysis of the factors that affect AI adoption in organizations. This will help to identify the barriers and enablers of AI adoption and provide insights into how organizations can effectively implement AI. Furthermore, the framework can be used to compare and contrast different organizations' experiences with AI adoption, and to identify best practices that can inform future adoption efforts.

ii. The DOI theory

It can inform the research proposal by providing a framework for understanding the adoption of AI within a social system. The theory can be used to identify the different categories of adopters and their characteristics, which can inform the development of strategies to encourage adoption among different user groups. By understanding the patterns of adoption over time, the research can also identify potential barriers to adoption and develop targeted interventions to overcome them.

Additionally, the DOI theory emphasizes the importance of innovation acceptance for the sustainability of the innovation. This can be applied to the adoption of AI, where the research proposal can focus on identifying the factors that influence acceptance of AI within organizations and developing strategies to ensure long-term sustainability of the technology. For example, the research can investigate how to foster a culture of acceptance of AI within organizations and how to ensure that employees are trained and supported to use the technology effectively.

2.4 Summary

As per a literature review, there exists a gap in knowledge concerning the facilitative factors of AI adoption in businesses, as well as their interplay and influence on the decision to implement AI. Thus, in order to enhance the comprehension of the success factors that affect AI adoption at the organizational level, this study suggests a research approach based on the TOE framework and the DOI theory.

CHAPTER THREE: METHODOLOGY

3.1 Introduction

According to Creswell (2013), a quantitative approach is appropriate when researchers need to measure or quantify a research problem or when they seek to test a hypothesis or theory. This methodology emphasizes the use of numerical data, statistical analysis and the testing of hypotheses (Bryman, 2012). The aim is to draw generalizable conclusions from a representative sample that can be applied to a larger population (Babbie, 2016). This approach is often used to explore relationships between variables or to test the effectiveness of interventions (Creswell, 2013). Common data collection methods include surveys, experiments, and secondary data analysis (Bryman, 2012). The quantitative approach provides a structured and systematic way of collecting and analyzing data that can yield precise and reliable results (Babbie, 2016).

3.2 Research Design

The descriptive survey research design was utilized in this study as it was the most appropriate methodology to analyze the primary subject matter. The research hypotheses were defined and tested through the collection and analysis of data. The results of this research will provide valuable insights into the research problem and will help to inform future studies in this area.

3.3 Study Area

The study was conducted in Kenya and focused on institutions that have adopted or are in the process of adopting Artificial Intelligence applications as part of their operational strategies.

3.4 Target Population

Data was targeted to be gathered from 500 senior managers in Both private and public companies who were directly in charge of the information systems in order to evaluate the model.

3.5 Sampling Technique

Systematic sampling technique was used in the research since there was a specific target population.

3.6 Sample Size

The intended participants are executives, particularly those who are directly in charge of information systems in Kenyan private and public companies. A representative sample of Kenyan industry from a variety of levels, backgrounds, gender, age, and geographic groups was to be recruited. The capacity to access a sizable number of respondents with widely disparate qualities, such as position, degree of education, and geographic area in Kenya. The sample size used is the same as the total population. Which was 500 because we were able to reach to them in time and the accuracy of the information is maximized.

3.7 Measurement of Variables

A 7-point Likert scale, from "I strongly agree" (7 points) to "I strongly disagree" (1 point), is used to assess these items and gather the majority of replies. The intended participants are executives, particularly those who are directly in charge of information systems in Kenyan private and public companies.

3.8 Research Instrument

In order to reach a wide number of possible participants, this study conducted a mail survey of significant Kenyan enterprises. The usage of the LinkedIn.com database gives advantages such as the ability to reach a big number of respondents with extremely diversified characteristics such as position, educational level, and geographical location within Kenya, allowing the results to be more generalizable.

3.9 Validity of Measurements.

Based on the findings of the expert interviews, the questionnaire items were revised and thoroughly pre-tested in order to assess the validity of the content. A total of 37 items were operationalized as indicators based on eleven constructs: compatibility, relative advantage, complexity, management support, organisation size, management ability, organisational willingness, government participation, market uncertainty, competitive pressure, and supplier partnership.

3.10 Reliability of Measurements

The researcher used internal consistency where the consistency of the measurement itself was getting the same results from different parts of a test designed to measure the same thing. This was achieved by:

i. Application of the methods consistently.

ii. Standardizing of the conditions of the research.

3.11 Data Collection Technique

We first did a thorough literature study, then used a quantitative approach to gather data from a survey in order to empirically test the proposed framework. Academic publications on technology readiness and AI underwent a thorough analysis. To bolster the accumulative research, elements that had been approved and evaluated in earlier investigations were utilised. Cruz-Jesus et al. (2017), Ahmadi et al. (2015), and Lay (2017). Using earlier research by Picoto et al(2014)., items to measure managerial challenges and organisational readiness characteristics were developed expressly for this study. Wright et al. (2017). To the best of our knowledge, none of the constructs utilised in these studies were focused on the adoption of AI, despite the TOE having been used in numerous IT adoptions at the corporate level. In order to determine whether the items were appropriate for evaluating framework dimensions in the context of this study, a pre-test survey was undertaken.

A representative sample of Kenyan industry from a variety of levels, backgrounds, gender, age, and geographic groups was to be recruited. The capacity to access a sizable number of respondents with widely disparate qualities, such as position, degree of education, and geographic area in Kenya, this was a benefit of using the LinkedIn.com database, and this can make the results more generic. All sectors received a total of 500 invitations written in English. With 10 missing data points, there were 203 total LinkedIn responses. In Chen's opinion (2018), 193 legitimate responses remained after these responses were excluded, which is still a valid sample for quantitative analysis.

3.12 Data Analysis

This study employs structural equation modelling (SEM) to analyse sample data and evaluate model fit. Chin and Marcolin(1995) created SEM, a method for high-quality statistical analysis of multivariate data, in the second generation. Analysis of Moment Structures (AMOS), a covariance-based method for analysing models with variables that have measurement errors, is used in SEM Gefen and Straub (2000). The study combines multivariate and regression analysis to examine concept linkage and factor analysis. In this work, the measurement model and the structural model are investigated using SmartPLS 3.3. The structural model shows the latent variables' potential causal links, whereas the measurement model shows the relationships between constructs (latent variables) and their indicators (observed variables) Chin et al (2003).

CHAPTER FOUR: FINDINGS AND DISCUSSION

4.1 Introduction:

In this study, we propose a measurement model for evaluating the success elements of AI adoption. The measurement model's adequacy is determined by analysing the measurement instrument's reliability, construct validity, convergence validity, and discriminant validity.

Measurement Model:

Eleven latent constructs (factors) and associated observable variables (indicators) are measured in the proposed model. The indicators under each construct about the success elements of AI adoption are then discovered and confirmed using factor analysis. Several signs are removed because their factor loadings are too low (0.4) or they are included in crossing loadings.

The Kaiser-Meyer-Olkin (KMO) coefficient is 0.829, indicating that the sample size is adequate for factor analysis. The Bartlett's test result (Sig. = 0.000) implies that the factor analysis is appropriate. The 37 observation variables are used to extract eleven components, and the calculated variance is 72.168 percent (more than 50%).

Confirmatory factor analysis (CFA) results demonstrate that all pathways linking the remaining observable variables and constructs are significant at $p<0.001$. The percentage of variance retrieved explains the construct validity of a model, according to Fornell and Larcker (1981). Each indicator explains between 50% and 80% of the overall variance.

The Cronbach's Alpha (CA) value for each construct is shown in Table 1. The composite reliability measures the scales' internal consistency (CR). It is a more precise measure of dependability, recommended by Gopal and Chin (1995) and Straub and Gefen (2000). All of the CR values for each construct are more than the threshold of 0.7, establishing the model's building reliability.

Convergent validity assesses the consistency of many items and is calculated using the extracted mean variance (AVE). Furthermore, at $p<0.001$, all derived standard loads are statistically significant, which is greater than the permitted magnitude of 0.50, as recommended by Chin and Marcolin (1995).

Table 1. Items and descriptive statistics.

Critical	Sub-Critical	Code	CA	R-Square	Loading
	Technical compatibility	CPA	0.926		0.868
		CPA1			***
		CPA2			0.890
		CPA3			***
		CPA4		0.753	0.915
				0.791	***
				0.837	0.869
				0.755	***
	Relative advantage	RAD	0.935		0.741
		RAD1			***
		RAD2		0.549	0.740
Technological context				0.548	***
		RAD3		0.695	0.834
					***
		RAD4		0.725	0.851
					***
	Technical complexity	CPL	0.831		
		CPL1		0.744	0.863
					***
		CPL2		0.839	0.916
					***
		CPL3		0.733	0.856
					***
		CPL4		0.749	0.865
					***
	Managerial support	MSU	0.808		
		MSU1		0.708	0.841
Organizational context				0.681	***

		MSU2		0.716	0.825
		MSU3			***
					0.846
					***
	Managerial capability	MCP	0.911		0.866
		MCP1			***
		MCP2			0.901
		MCP3		0.751	***
				0.812	0.834
				0.696	***
	Organization size	ORS	0.831		
		ORS1		0.596	0.702
					***
		ORS2		0.689	0.816
					***
		ORS3		0.682	0.866
					***
	Organizational readiness	ORE	0.869		
		ORE1		0.695	0.834
					***
		ORE2		0.725	0.851
					***
		ORE3		0.708	0.841
					***
		ORE4		0.681	0.825
					***
	Government involvement	GIV	0.875		0.689
		GIV1			***
		GIV2		0.716	0.825
		GIV3		0.602	***
External environment				0.735	0.789

				***
Market uncertainty	MUC	0.892		0.737
	MUC1			***
	MUC2			0.896
	MUC3		0.689	***
			0.682	0.744
			0.593	***
Competitive pressure	CPR	0.901		
	CPR1		0.786	0.769 ***
	CPR2		0.753	0.920 ***
Vendor partnership	VPA	0.809		
	VPA1		0.493	0.702 ***
	VPA2		0.786	0.887 ***
	VPA3		0.753	0.868 ***
	VPA4		0.787	0.887 ***

Note: *** indicates significant at 1% level of significance based on t-statistics.

Table 2. Result of measurement model.

Construct	**Composite Reliability (CR)**	**Variance Inflation Factor (VIF)**	**Average Variance Extracted (AVE)**
Technical compatibility (CPA)	0.926	1.155	0.757

Relative advantage (RAD)	0.936	2.659	0.784
Technical complexity (CPL)	0.841	1.741	0.641
Managerial support (MSU)	0.929	1.275	0.766
Managerial capability (MCP)	0.813	1.546	0.593
Organization size (ORS)	0.901	2.293	0.752
Organizational readiness (ORE)	0.837	1.522	0.633
Government involvement (GIV)	0.871	2.205	0.629
Market uncertainty (MUC)	0.876	2.326	0.701
Competitive pressure (CPR)	0.852	2.490	0.677
Vendor partnership (VPA)	0.904	1.755	0.705

To determine the discriminant validity of constructs, the Fornell-Larcker criterion is used, which states that the square root of AVE should be greater than the correlations between the Fornell and Larcker (1981) components. As shown in Table 2, the square root of the AVE of each latent construct, shown in bold on the diagonal, is greater than the correlations between the latent constructs in the corresponding columns and rows. As a result, the discriminant validity of the construct is established. In addition, the inter-item correlations are all less than 0.90 Bagozzi et al. (1991) and demonstrate that each concept is different. While certain constructs have marginally low levels of construct validity, most constructs have a reasonable level of validity and reliability.

When there is a large degree of correlation between predictor variables, it causes erroneous and unstable estimations of regression coefficients. To identify multicollinearity, the variance inflation factor (VIF) is utilized, which is defined as the amount by which the standard error rises due to collinearity. The correlation table for evidence of multicollinearity between the eleven latent variables (Table 2) reveals that all VIF with latent variable scores are less than the 5.0 Tabri and Elliott criterion (2012). As illustrated in the graph, VIF values range from 1.155 to 2.659. (Table 3). As a result, the predictor variables are not multicollinear.

Table 3. Latent variable correlations

Construct	1	2	3	4	5	6	7	8	9	10	11
CPA	**0.883**										
RAD	0.720 **	**0.895**									
CPL	0.311 **	0.323 **	**0.823**								
MSU	−0.441 **	−0.329 **	−0.108	**0.866**							
MCP	0.192 **	0.289 **	0.442 **	0.018	**0.791**						
ORS	0.512 **	0.571 **	0.535 **	−0.211 **	0.379 **	**0.876**					
ORE	0.259 **	0.258 **	0.545 **	−0.07	0.463 **	0.411 **	**0.785**				
GIV	0.541 **	0.590 **	0.504 **	−0.144 *	0.404 **	0.591 **	0.443 **	**0.802**			
MUC	0.576 **	0.669 **	0.390 **	−0.281 **	0.270 **	0.585 **	0.296 **	0.544 **	**0.835**		
CPR	0.644 **	0.688 **	0.312 **	−0.264 **	0.283 **	0.547 **	0.286 **	0.519 **	0.654 **	**0.819**	
VPA	0.554 **	0.568 **	0.240 **	−0.285 **	0.208 **	0.476 **	0.213 **	0.379 **	0.501 **	0.601 **	**0.839**

4.2 Assessing the Structural Model and Hypotheses Testing

The structural model was examined in order to validate the putative relationships. Following that, the structural model was analysed using the structural equation model SEM-PLS. The measurement model's path coefficients, coefficient of determination, and predictive significance were tested for verification and validation. The route coefficients method Economics 2022, 10, 129 11 of 16 encompasses the links between the constructs. Table 4 shows that 11 hypotheses (*H0a, H0b, H0c, H0d, H0e, H0f, H0g, H0h, H0i, H0j, and H0k*) have substantial paths leading to the endogenous variable, while two (H2c and H3c) are rejected (path coefficients < 0.20). R^2 is the coefficient of determination, and f2 is the percentage of variance in the endogenous construct that is explained by all external constructs. Results above 0.670 are regarded as substantial in Leguina (2015), 0.330 as moderate, and 0.190 as weak. According to our findings, the R^2 score is 0.872, which denotes a high degree of prediction accuracy. Leguina (2015) classifies f2 values between 0.02 and 0.15 as low, between 0.02 and 0.15 as high, between 0.02 and 0.35 as medium, and below 0.02 as weak. In accordance with our research, f2 of (CPA, ORE, MCP, and MSU) is high, f2 of OS is low (less than 0.02), but f2 of CPR and GIV is less than 0.02.

Table 4. Hypothesis test results.

Hypothesis Paths		Standard Coefficient (β)	Path *p*-Value	Results
H0a	Technical compatibility —> AI adoption	0.803	***	Support

H0b	Relative advantages —> AI adoption	0.157	0.019 **	Support
H0c	Complexity —> AI adoption	−0.223	***	Support
H0d	Managerial support —> AI adoption	0.206	0.011 **	Support
H0e	Managerial capability —> AI adoption	0.416	***	Support
H0f	Organizational size —> AI adoption	−0.028	0.703	Not support
H0g	Organizational readiness —> AI adoption	0.758	***	Support
H0h	Government involvement —> AI adoption	−0.304	***	Support
H0i	Market uncertainty —> AI adoption	0.149	0.047 **	Support
H0j	Competitive pressures —> AI adoption	0.036	0.519	Not support
H0k	Vendor partnerships —> AI adoption	0.113	0.048 **	Support

4.3 Discussion

The main aim of the study was to identify the critical factors affecting artificial intelligence application to adopt in Kenya. The study concentrated on the TOE framework and DOI theory to acquire a deeper understanding of the success factors impacting the adoption of AI at the organizational level in order to accomplish the research goal. The study's structural equation modelling is used to analyse the data. The findings indicate a strong correlation between managerial skill and AI innovative traits. Better management capabilities improve the IT environment for AI adoption and lessen the complexity of implementing AI technologies. These findings imply that, while government participation and vendor partnerships are important drivers in AI adoption, corporate scale and competitive forces do not. This means that strong vendor relationships and supplier alliances can aid businesses in implementing AI, while government participation can affect AI adoption. The adoption of AI and market uncertainty or competitive pressure do not, however, correlate positively.

One goal of this study was to look at AI adoption from an organizational viewpoint because the conceptual foundation for its adoption is still in its early stages. According to the statistics, management support is one of the best indicators of AI adoption in the organizational setting. The findings of this study are in line with those of Leach (2021), Zhu and Kraemer (2005), and other researchers who discovered that managerial support has a large favorable impact on the adoption of new technology. Additional support for the role people play in the adoption of AI is provided by our findings. Organizational readiness is significant because it suggests that technological capabilities including technological infrastructure, data structure, and human capital are essential for determining whether a corporation embraces AI or not. The findings show that firms with higher levels of readiness frequently embrace AI at higher rates. The attempt to create hybrid-enabled capabilities to support artificial intelligence technology is thus one of the traits of AI adopters. Vietnamese organizations' success in overcoming AI hurdles can be explained by the possibility that they have the necessary relevant experience.

Interestingly, this study discovered that there was no statistically significant correlation between firm size and AI use. These findings are in opposition to those of Walczak (2018), who discovered that organizational scale had a positive impact on AI and the adoption of cutting-edge ideas. The increase in smaller tech-inspired firms may help to explain this. Large businesses can also be inhibited by structural inertia due to the several layers of bureaucracy they contain. The findings of this study indicate that huge organizations do not predominate in the use of AI. Our findings demonstrate that considering company size as a crucial factor alone is insufficient to comprehend the adoption of AI. The increase in smaller tech-inspired firms may help to explain this.

CHAPTER FIVE: SUMMARY, CONCLUSIONS AND RECOMMENDATIONS

5.1 Introduction:

This study explores the adoption of AI applications at the organizational level and integrates well-established theories into a novel innovation. Our research provides a foundation for future studies investigating why and how organizations use AI. It also serves as a starting point for further examination of AI adoption across various industries. This contribution highlights the importance of offering guidance and tools for researching the topic of AI adoption and provides an overview of potential research topics.

5.2 Summary of Major Findings:

Our research offers valuable insights into the components that explain the AI-specific aspects influencing an organization's intention to adopt AI. To begin, we provide a definition of AI from both an information system (IS) and organizational standpoint. Furthermore, this study builds on existing research on technology adoption by blending well-known theories and in-depth literature on AI.

As demonstrated in the literature review, there has been little research into identifying the factors that lead enterprises to adopt AI. Therefore, this study supports the organizational context and innovative features that influence AI adoption. The findings confirm that IS theories, such as the technology-organization-environment (TOE) framework and the diffusion of innovation (DOI) model, can provide a comprehensive understanding of successful AI adoption at the organizational level, though with some limitations.

5.3 Conclusions:

The study's findings have important implications for organizations looking to adopt AI applications. The study provides valuable insights into the factors influencing AI adoption and emphasizes the importance of considering organizational context and innovative features when making adoption decisions. The use of established theories, such as the TOE framework and the DOI model, can aid in understanding and predicting successful adoption outcomes.

5.4 Recommendations for Policy or Practice:

Based on our study's findings, we recommend that organizations seeking to adopt AI applications should consider the organizational context and innovative features that influence adoption decisions. Additionally, policymakers should consider the potential impact of government regulations on AI adoption. Finally, we suggest that future research should explore the acceptance and actual application of AI in other contexts, such as Vietnam and beyond. Overall, our study provides significant contributions from both theoretical and practical perspectives and suggests exciting future research options.

5.5 Recommendations for Further Research:

While this study offers valuable insights into AI adoption, there remain some gaps in our understanding of this topic that require further investigation. For instance, future research could examine the impact of government laws and regulations on AI adoption, as well as how cultural and societal factors influence AI adoption decisions. Additionally, future research could explore how AI adoption affects organizational outcomes such as productivity and competitiveness. Finally, research could investigate how AI adoption might impact employment and labour markets, and what implications this might have for organizations and society at large.

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APPENDICES

Appendix 2: Proposed Research Schedule

	Time in Months						
Research Activity	1	2	3	4	5	6	7
Acceptance of research proposal							
Talk with the representatives of the study area							
Development of research tools							
Sample selection							
Validation of equipment							
Data collection							
Data entries and analysis							
Thesis report writing							

Questionnaire

Hello Senior Manager,

We are conducting a study on the adoption of AI applications in companies, and we would like to invite you to participate in our survey. This survey aims to investigate the significant factors that influence the adoption of AI applications in companies. We appreciate your valuable input, which will help us gain insights into how AI is being adopted in the industry. Your participation in this survey is voluntary, and your responses will be kept confidential. Let's get started!

Section 1: Technical Compatibility

1. On a scale of 1-5, with 1 being "not important" and 5 being "extremely important", how important do you think technical compatibility is in the adoption of AI applications in your company?
   - ☐ 1
   - ☐ 2
   - ☐ 3
   - ☐ 4
   - ☐ 5
2. Could you give us an example of how technical compatibility has affected the adoption of AI applications in your company____
3. Section 2: Relative Advantage 3. On a scale of 1-5, with 1 being "not important" and 5 being "extremely important", how important do you think the relative advantage of AI applications is in the adoption decision-making process in your company?
   - ☐ 1

- ☐ 2
- ☐ 3
- ☐ 4
- ☐ 5

4. Could you provide an example of how the perceived relative advantage of AI applications has influenced the adoption decision-making process in your company?

____
____
____
____
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____
____

Section 3: Technical Complexity 5. On a scale of 1-5, with 1 being "not important" and 5 being "extremely important", how important do you think technical complexity is in the adoption of AI applications in your company?

- ☐ 1
- ☐ 2
- ☐ 3
- ☐ 4
- ☐ 5

6. Could you share an example of how technical complexity has affected the adoption of AI applications in your company?

____
____
____
____

____

Section 4: Managerial Support 7. On a scale of 1-5, with 1 being "not important" and 5 being "extremely important", how important do you think managerial support is in the adoption of AI applications in your company?

- ☐ 1
- ☐ 2
- ☐ 3
- ☐ 4
- ☐ 5

Could you give us an example of how managerial support has influenced the adoption decision-making process in your company? ____

Section 5: Managerial Capabilities 9. On a scale of 1-5, with 1 being "not important" and 5 being "extremely important", how important do you think the managerial capabilities of your company are in the adoption of AI applications?

- ☐ 1
- ☐ 2
- ☐ 3
- ☐ 4
- ☐ 5

Could you provide an example of how the managerial capabilities of your company have influenced the adoption decision-making process for AI applications? ____

Section 6: Organizational Size 11. On a scale of 1-5, with 1 being "not important" and 5 being "extremely important", how important do you think the organizational size is in the adoption of AI applications in your company?

- ☐ 1
- ☐ 2
- ☐ 3
- ☐ 4
- ☐ 5

Could you share an example of how the organizational size has influenced the adoption decision-making process for AI applications in your company? ____

Section 7: Organizational Readiness 13. On a scale of 1-5, with 1 being "not important" and 5 being "extremely important", how important do you think organizational readiness is in the adoption of AI applications in your company?

- ☐ 1
- ☐ 2
- ☐ 3
- ☐ 4
- ☐ 5

Could you give us an example of how organizational readiness has influenced the adoption decision-making process for AI applications in your company? ____

Section 8: Government Involvement 15. On a scale of 1-5, with 1 being "not important" and 5 being "extremely important", how important do you think government involvement is in the adoption of AI applications in your company?

- ☐ 1
- ☐ 2
- ☐ 3
- ☐ 4
- ☐ 5

Could you share an example of how government involvement has influenced the adoption decision-making process for AI applications in your company? ____

Section 9: Market Uncertainty 17. On a scale of 1-5, with 1 being "not important" and 5 being "extremely important", how important do you think market uncertainty is in the adoption of AI applications in your company?

- ☐ 1
- ☐ 2
- ☐ 3
- ☐ 4
- ☐ 5

Could you provide an example of how market uncertainty has influenced the adoption decision-making process for AI applications in your company? ____

Section 10: Competitive Pressure 19. On a scale of 1-5, with 1 being "not important" and 5 being "extremely important", how important do you think competitive pressure is in the adoption of AI applications in your company?

- ☐ 1
- ☐ 2
- ☐ 3
- ☐ 4
- ☐ 5

Could you give us an example of how competitive pressure has influenced the adoption decision-making process for AI applications in your company? ____

Section 11: Vendor Partnership 21. On a scale of 1-5, with 1 being "not important" and 5 being "extremely important", how important do you think vendor partnership is in the adoption of AI applications in your company?

- ☐ 1
- ☐ 2
- ☐ 3
- ☐ 4
- ☐ 5

Could you share an example of how vendor partnership has influenced the adoption decision-making process for AI applications in your company? ____

Conclusion: Thank you for taking the time to complete our survey. Your feedback is valuable to us, and it will help us gain insights into the factors that influence the adoption of AI applications in companies. If you have any further comments or feedback, please feel free to share them with us in the space provided below. Thank you again for your participation!