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"Artificial Intelligence Adoption and Implementation in Palestinian Context: The Moderating Role of Strategic Leadership and the Perceived Attributes of Innovation"

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Dissertation Approval

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Declaration

I confirm that this dissertation, submitted for the award of PhD level degrees, is the work of my research except as indicated in the acknowledgments. I further declare that it hasn't been used for submission to any other university or institution for awarding a higher qualification.

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Dedication

In the name of Allah.

To my great teacher, Prophet Mohammed.

To my country, Palestine, and its beloved capital, my birthplace, and the delight of my heart, Jerusalem.

To the great martyrs and prisoners, living examples of sacrifice.

To my very dear parents, selfless to no end.

To my precious husband Eyad, whose unyielding hope and support shed light on my path.

To my beloved children: Ahmad, Malak, Tayma, Maria, and Talia.

To the whole family who represents love and generosity.

I humbly dedicate this dissertation.

Acknowledgment

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Additionally, I want to express my sincere gratitude to my friends and coworkers, for their unwavering encouragement and support.

Finally, I want to sincerely thank my husband and kids, who were my rock during this journey with their unfailing love and encouragement. Their belief in me enabled me to achieve this success.

Many thanks, Elham Mohmmad Nabhan

Abstract

Purpose: This study examines the relationships between ICT readiness factors, strategic leadership, and AI adoption within Palestinian MSMEs. It highlights the moderating roles of strategic leadership and perceived attributes of innovation in resource-constrained environments.

Methodology: A quantitative, cross-sectional approach was employed, involving 520 participants from various MSMEs in the West Bank of Palestine. Data was collected via structured questionnaires and analyzed using PLS-SEM and SPSS to evaluate hypotheses and validate constructs.

Result: the findings indicate that ICT readiness, encompassing hardware, software, infrastructure, and human resources, are significant drivers of AI adoption (β = 0.140, t = 2.544, and p-value of 0.006). Strategic leadership demonstrates a dual impact: positively influencing software and human resource alignment β = 0.114, β = 0.129 respectively, while negatively moderating infrastructure (β = -0.129) and hardware readiness (β = -0.072). Perceived innovation attributes like relative advantage and compatibility further enhance ICT readiness' influence on AI adoption (β = 0.146, t = 2.784, and p-value of 0.003).

Practical Implications: Policymakers and leaders in resource-constrained contexts can leverage these findings to design comprehensive ICT strategies, promote balanced leadership approaches, and address barriers to AI adoption.

Originality: This study contributes to the literature on the adoption of technology by focusing on a politically complex and resource-limited setting, offering actionable insights for enhancing MSMEs' innovation capacity through AI adoption.

Keywords: ICT readiness, AI adoption, strategic leadership, innovation attributes, Palestinian MSMEs, technology adoption, resource-constrained environments, quantitative analysis, PLS-SEM, developing economies

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List of Abbreviations

No.	Abbreviation	Meaning
1.	AI	Artificial Intelligence
2.	ICT	Information and Communications Technology
3.	ETAM	Extended Technology Acceptance Model
4.	ESCWA	United Nations Economic and Social Commission for Western Asia
5.	GDP	Gross Domestic Product
6.	UN	United Nations
7.	ICT-R	ICT readiness
8.	SL	Strategic Leadership
9.	ICT-H	ICT Hardware
10.	ICT-I	ICT Information
11.	ICT-P	ICT People and Human
12.	ICT-S	ICT System and Software
13.	PAI	Perceived attributes of innovation
14.	RA	Relative Advantage
15.	CO	Compatibility
16.	DOI	Diffusion of Innovation Theory
17.	SME	Structural Equation Modeling
18.	PCA	Principal Component Analysis
19.	ANI	Artificial Narrow Intelligence
20.	RPA	Robotic Process Automation
21.	NLP	Natural Language Processing
22.	AGI	Artificial General Intelligence
23.	ASI	Superintelligent AI
24.	IoT	Internet of Things
25.	TAM	Technology Acceptance Model
26.	UTAUT	Unified Theory of Acceptance and Use of Technology
27.	TOE	Technology-Organization-Environment
28.	GDPR	General Data Protection Regulation

29.	CMM	Capability Maturity Model
30.	AIMM	AI Maturity Models
31.	TRL	Technology Readiness Levels
32.	H	Hypothesis
33.	VR	Virtual Reality
34.	RBV	Resource-Based View
35.	HRM	Human Resource Management
36.	KBV	Knowledge-based View Theory
37.	STEM	Science, Technology, Engineering, and Mathematics
38.	INGO	International Non-governmental Organization
39.	MSME	Micro, Small, and Medium Enterprises
40.	SMEs	Small and Medium Enterprises
41.	VMT	Virtual Math Teams
42.	ERP	Enterprise Resource Planning
43.	VRIN	valuable, Rare, Inimitable, and Non-substitutable
44.	E-HRM	Electronic - Human Resource Management
45.	PCBS	Palestinian Central Bureau of Statistics
46.	PITA	Palestinian Information Technology Association
47.	IRB	Institutional Review Board
48.	EFA	Exploratory Factor Analysis
49.	CFA	Confirmatory Factor Analysis
50.	AVE	Average Variance Extracted
51.	VIF	Variance Inflation Factors
52.	TLI	Tucker-Lewis Index
53.	RMSEA	Root Mean Square Error Of Approximation
54.	SRMR	Standardized Root Mean Square Residual
55.	Q	Question
56.	α	Cronbach's Alpha
57.	CR	Composite Reliability
58.	HTMT	Heterotrait-Monotrait
59.	R^2	Coefficient of Determination

60.	Q^2	Predictive Relevance
61.	f^2	Effect Size
62.	β	Path Coefficient
63.	FSD	Full Self-Driving

Chapter One

Introduction

1.1 Introduction and Background

In recent years, artificial intelligence (AI) has been having a tremendous impact on the global technology landscape, transforming many fields and altering the way businesses conduct operations. AI uses technologies to enable machines to perform the type of tasks that human beings would usually execute, such as visual perception, speech recognition, decision-making, and translation of languages (Naved, 2023). The implementation of AI within the context of business operations allows for the utilization of its considerable benefits, including improved efficiency, decision-making, and competitive advantage (J. Yang et al., 2024). In the current age of technological innovation, the increased recognition of the role of AI in fostering the development of businesses has resulted in it becoming one of the most critical sources of competition in a wide range of industries, and its adoption has become a critical strategic priority across industries (Pumplun et al., 2019a).

Several factors have driven the growing integration of AI in business and organizational contexts. For example, following the rapid growth of the amount of data generated and available, AI instruments can analyze extensive data and extract valuable conclusions from the analysis (Barua et al., 2024; Naved, 2023). It performs multiple tasks for businesses, such as facilitating decision-making processes, optimizing internal procedures, and identifying new market opportunities (Naved, 2023). Also, the growing capacities of computing systems and the capabilities of new algorithms have improved the accessibility of AI tools and decreased their cost. Therefore, even small and medium businesses can benefit from them rather than only being available to larger organizations (Ghadiyaram & Bovik, 2017). Further, as the speed of changes in markets and the overall business environment rises, managers offer a growing interest in innovative strategies helping to increase operational efficiency and improve customer experiences (Asikin Shaharuddin et al., 2023).

Recently, AI has made its way into almost all industries, including banking and financial services, healthcare, and education. For example, AI has made extensive progress in the financial services and banking sector for its potential to revolutionize operations and customer experiences (Kaur & Singh, 2024). AI-powered chatbots and virtual assistants have become popular in commercial institutions to deliver custom support and financial advice to customers (Saxena et al., 2023). They may be used to analyze customer data and present personalized product suggestions to customers, as well as to assist with regular transactions. Similarly, the development of AI has brought significant advances in the healthcare sector. Some of the applications of AI in healthcare are diagnostic support, generating personalized treatment plans, and identifying at-risk patients (Jebreen et al., 2024). However, the integration of AI into healthcare also has its negative issues. Some examples of the negative issues that can result from the use of AI in healthcare are the violation of patient privacy and the potential bias in AI-driven judgment and decision-making (Baihakki & Qutayan, 2023) . In the context of education, the experience of the United States integrating AI technologies in the classrooms, such as virtual tutors and chatbots that can provide 24/7 support to students, answer questions, and offer guidance, is an ideal example of how AI has changed the paradigm of teaching and improving the productivity of teachers (Almaiah et al., 2022a).

While AI provides many promises and benefits at both individual, organizational, and national levels, the integration of new technology such as AI is influenced by many factors, including ICT readiness (Chanyagorn & Kungwannarongkun, 2011), attributes of technology innovation (Cubric, 2020; Roger, 1995), strategic leadership (Jaiswal et al., 2022; Neher et al., 2023; Özdemir et al., 2020), and the availability of financial resources (Varian, 2018) and human capital (Nguyen & Tran, 2019). Mo (2012b) posited that ICT development consists of several key components, including infrastructure, hardware, software, information systems, and skilled human resources. These components serve as the foundation for organizations to effectively integrate ICT, such as AI, in their operations. Further, Nguyen and Tran (2019) argued that AI implementation requires strategic leadership that goes beyond oversight, and therefore, understanding how AI works and integrating it across various activities is paramount to leaders. The perceived attributes of diffusion of innovation theory Miller (2015a) emphasized the importance of the relative advantage, compatibility, complexity, observability, rate of adoption of innovation, and trialability attributes of innovation in the acceptance and implementation of any technology-related innovation such as AI. The combination and interaction of these factors (ICT readiness, strategic leadership, and attributes of innovation) among themselves represent the conceptual framework of focus in this research.

In the Palestinian context, the adoption and implementation of AI present both unique challenges and opportunities (ESCWA, 2022; Herzallah, 2016). As a developing nation, Palestine faces obstacles in adopting advanced technologies such as AI (ESCWA, 2022), such as limited access to resources, infrastructure constraints, and minimal specialization in AI development and implementation are significant barriers (Herzallah, 2016). In line with this, ICT readiness has been viewed as one of the drivers of developing countries' acceptance of advanced technologies such as AI (Chanyagorn & Kungwannarongkun, 2011; Demaidi, 2023; MWAPWELE et al., 2019). As for Palestine, the relationship between ICT readiness and AI adoption is multifaceted. Although precise data on Palestine is absent, general trends confirm that ICT readiness appears to be overturned by AI adoption(Musleh, 2022). When broadened to the context of the issues of new technologies, this relationship is impacted by the degree of ICT infrastructure development, digital skills, and education, as well as economic factors (Morrar et al., 2019; Nawastheen et al., 2023).

Additionally, it should be noted that organizational readiness for the implementation of AI technologies received a significant influence depending on leadership styles and attitudes (Pumplun et al., 2019b). For example, transformational leadership, which implies inspiring employees to adopt changes and actively motivating and supporting them, proved to be most effective in promoting technological developments and innovations (Almarzooqi, 2019; Bankins et al., 2024). Moreover, the competence of leaders in terms of communication, the ability to present the benefits to employees, reduce the level of anxiety and resistance associated with the potential loss of their position, and adequate training and support of personnel are crucial for promoting AI adoption and implementation (Kahenda Vita & Muathe, 2023). Therefore, A critical factor in AI adoption in Palestine is the moderating impact of strategic leadership. Such leadership plays a crucial role in overcoming complex barriers, including limited resource perceptions, skills gaps, and change resistance (Boal and Hooijberg, 2001; Mjaku & c, 2020; Pumplun et al., 2019b). Strengthened technological integration efforts brought about by strategic leadership contribute to a heightened culture of innovation (Musleh, 2022).

The perceived attributes of innovation are vital in the adoption and implementation of AI technologies (Baytak, 2023). According to the Diffusion of Innovation theory, five such attributes affect the rate of adoption: relative advantage, compatibility, complexity, trialability, and observability (Almaiah, Alfaisal, et al., 2022a; Miller, 2015a). Perceived attributes of innovation have a decisive impact on shaping the adoption and follow-through strategies for AI (Baytak, 2023). This is informed by the Extended Technology Acceptance Model (ETAM), which explains the significance of perceived ease of use and perceived usefulness as critical determinants of behavioral intentions when evaluating adopting AI in Palestinian education and other areas (Jasimuddin et al., 2017; Khalid et al., 2024).

While there is a significant amount of research on adopting and implementing AI, there remain significant gaps in knowledge, particularly in the case of developing economies, including Palestine (Adebayo Olusegun Aderibigbe et al., 2023; Bilokopytova & Karim, 2023; Demaidi, 2023; ESCWA, 2022; Shahadat et al., 2023b, 2023a). More comprehensive studies that would account for the specificity of the economic, cultural, and technological context of the region would be beneficial in identifying the challenges and opportunities of AI adoption. At this point, there exists limited research on the role of strategic leadership regarding AI adoption in Palestine as a developing country and emerging market (Adebayo Olusegun Aderibigbe et al., 2023; Bilokopytova & Karim, 2023; Demaidi, 2023; Shahadat et al., 2023b, 2023a), which is an important essential gap in knowledge that can and should be filled.

Consequently, this research aims to investigate the factors influencing artificial intelligence adoption and implementation in the Palestinian context with a specific focus on the moderating role of strategic leadership and perceived attributes of innovation, such as relative advantage and compatibility, by exploring the relationship between ICT readiness factors (infrastructure, hardware, information systems/software, and human resources) and the adoption of AI. The study seeks to provide comprehensive insight into the challenges and opportunities of AI integration in the context of a developing economy marked by political instability and the unique socio-economic situation of the Palestinian territories.

As such, the study seeks to provide valuable insights for policymakers, business leaders, and academics by adding to the existing body of knowledge on the works of literature associated with the adoption of technology within the context of developing economies, taking into account their complex political nature, resource constraints data quality, skills gaps, and ethical concerns.

Additionally, the results of this study will be used for the development of effective AI adoption strategies matched to the specific characteristics of the Palestinian economy so that such findings will create a basis for a theoretical model that can serve as a foundation for similar developing economies. In the long term, this research will bridge the existing gap between the theoretical models of the process of technology adoption and the actual implementation of the AI system, one of the most advanced technologies, in a politically and economically challenging environment, foster innovation and economic growth in Palestine and beyond.

1.2 Study Significance and Justification

The significance of this study is a result of the unprecedented growth in the adoption and utilization of artificial intelligence (AI) in both private and public landscapes. It builds on the concepts and variables in the conceptual model this study proposes, focusing on the moderating roles of strategic leadership and perceived attributes of innovation and the impact of ICT readiness factors on AI adoption in Palestinian organizations. This study contributes to understanding AI uptake in developing nations by examining ICT preparedness aspects, analyzing strategic leadership engagement, and assessing perceived attributes of innovation. This research feeds into the existing knowledge regarding technological adoption by revealing the complex interplay between technological infrastructure, human factors, and organizational characteristics in the context of AI implementation (Mehmood et al., 2020; Paun et al., 2024). This study complements the gaps in the current literature and serves as the base on which one can establish factors that affect the implementation of AI together with the set of opportunities and challenges for organizations in developing countries concerning the incorporation of AI (Demaidi, 2023; Madan & Yadav, 2016; Solomon Nsor-Anabiah et al., 2019).

The importance of this study is also derived from its ability to employ a multidimensional perspective and focus on the contextual factors relating to the integration of AI in the state of Palestine. When integrated with the existing adoption models, these ICT readiness factors provide a holistic view of the issues and opportunities of integrating AI in

Palestine (Abdelmoneim et al., 2024; ESCWA, 2022; Mosleh et al., 2023). This research addresses AI from a conflict-affected region perspective (Raddad & Samat, 2016), thereby expanding global literature on technology adoption. The Palestinian scope of this study and its focus on the integration of AI at individual, organizational, and national levels provides a distinct perspective on the prospects and challenges that any developing country with troubled internal and geopolitical reality can face while attempting to achieve its goals (Demaidi, 2023; Madan & Yadav, 2016; Solomon Nsor-Anabiah et al., 2019; Xiang et al., 2023). This research seeks to support Palestinian efforts to respond to the challenges of AI adoption and aid in identifying efficient strategies for data management to facilitate the use of AI in different fields, potentially contributing to national development and self-reliance (ESCWA, 2022). AI technologies can empower minority groups by raising awareness of violations of the rights of minorities, upholding people's culture, documenting human rights violations, and promoting education in conflict-affected areas (Agwanda et al., 2021; ESCWA, 2022; Maigari, 2022). Besides, AI has also enhanced conflict management and peaceful resolution in regions prone to cyclical conflicts (Agwanda et al., 2021; Maigari, 2022). Establishing AI adoption in Palestinian territories requires opening new opportunities for dialogue and coordination that may define the region's further development (ESCWA, 2022). Overall, this study may lead to positive changes, thereby enhancing Palestinian technology and stimulating increased invention, technological advancement, and economic growth despite political and economic crisis conditions. Apart from strengthening the theoretical background of the AI phenomenon, it is possible to enhance the practical application of AI in Palestine and offer critical insights to other developing countries facing similar challenges in the digital age.

Practically, the results of the present research will be of great significance to policymakers in the business and educational spheres in Palestine. Given that the global economy is becoming more and more dependent on AI-driven solutions (Chi et al., 2020; Stix, 2022), defining the factors that either enhance or prevent the promotion of AI in Palestine appears to be a crucial step in ensuring the country's economic competitiveness and technological advancement. More importantly, in the region where the scarcity of resources is a common problem (ESCWA, 2022; Tadj et al., 2023), the information obtained from the study can be used to introduce tools and strategies that will help make the distribution of resources more reasonable and improve outcomes across various sectors. The potential implications of this research are extensive. For society, it might increase the overall understanding of the development of AI and what it could bring to a developing country in the Middle East. For policymakers, it might help to develop appropriate policies and programs to promote specific AI initiatives and, more importantly, help to create a Palestinian model that defines the AI developments in the region. For business, it might help to offer strategies and solutions that are tailored to AI implementation in the context of Palestine. For scholars and the academic community, it might contribute to the existing body of research on AI developments in developing countries and suggest the prospects of further comparative analysis.

Moreover, this research is timely and aligns with global tendencies. According to the worldwide research center of McKinsey, AI will contribute up to 14% to the global GDP by 2030 and has the potential to realize 48 of the 169 UN Sustainable Development Goals (Mansor et al., 2022). For Palestine, understanding how to adopt and implement AI effectively could be a crucial step toward economic advancement and technological competitiveness.

1.3 Problem Statement and Research Gap

While AI technologies are increasingly becoming critical engines to the competitiveness and growth of world economies worldwide (Păvăloaia & Necula, 2023), the Palestinian territories are characterized by serious hindrances to the technological infrastructure and development. Political instability, economic constraints, and lack of resources significantly affect the readiness of organizations to adopt and integrate AI technologies in their operations (Musleh, 2022). Nevertheless, there is a growing demand to apply such solutions to overcome local challenges and promote innovation within different industries. Multiple factors - socio-economic, cultural, and political - complicate the utilization of AI in Palestine, which in turn highlights the necessity of understanding how these factors interact with the adoption and integration of AI technologies (Musleh, 2022).

The one core dimension that has not been appropriately considered in the case of Palestine, where AI is concerned, is that of information and communications technology readiness. It involves several common key components, including infrastructure, hardware and software availability, information systems and data security, and human resources (Mircea et al., 2011). These elements of ICT readiness are likely to impact an organization's ability to efficiently adopt and implement AI technologies (Alsheibani et al., 2018; Martínez-Plumed et al., 2021). It is likely that the higher the degree of ICT readiness, the better equipped an organization is to address the challenges related to adoption of AI and take advantage of its benefits (Al-Ammary & Ghanem, 2024; Gao & Liu, 2023). In addition, the relationship between ICT readiness and technology is affected by two key factors, which are strategic leadership (Ka, 2023; Kahenda Vita & Muathe, 2023; Özdemir et al., 2020; Rowe, 2001) and the perceived attributes of innovation (Almaiah, Alfaisal, et al., 2022b; Baytak, 2023). They play an important role in facilitating technological change within organizations (Tarisayi, 2024). Leaders who have a clear vision of how AI can be used and who can effectively deal with resistance to change are in a better position to take advantage of the existing ICT performance and overcome adoption obstacles (Gao & Liu, 2023; Tarisayi, 2024).

Similarly, the perceived attributes of AI as a form of innovation, such as its relative advantage, compatibility, complexity, trialability, and observability, could moderate the relationship between ICT readiness and AI adoption in various ways (Almaiah et al., 2022b;

Baytak, 2023). For instance, organizations that perceive AI to have significant benefits, be compatible with existing systems, and, or be easy to implement may still realize a high probability of adopting AI despite the challenges on their level of ICT readiness. Similarly, the probability of an organization adopting AI would still be significant if the perceived magnitude of the relative advantage of AI was high for the companies (Gao & Liu, 2023).

The research gaps this research addresses are threefold. First, there is no specific research that aimed at discussing the question of AI adoption specifically in Palestine, as few studies examined the AI-related issues in general (ESCWA, 2022; Jebreen et al., 2024; Mosleh et al., 2023) Second, there is a lack of information on existing IT infrastructure in Palestine. Previous research discussed the problem of IT unpreparedness in the country but did not analyze what technologies can be implemented (ESCWA, 2022; Maitah & Hodrab, 2015; Morrar et al., 2019; Musleh, 2022). Since the proper infrastructure is critical for AI implementation(Adebayo Olusegun Aderibigbe et al., 2023; Martínez-Plumed et al., 2021), it is essential to comprehend what capabilities Palestinian organizations have. Thirdly, another critical factor in the adoption of AI is related to the study of the role of strategic leadership in AI technology implementation. In general, it is well established that leadership is one of the main factors affecting technological change (Ka, 2023; Kahenda Vita & Muathe, 2023; Özdemir et al., 2020; Rowe, 2001). However, none of the studies analyzed how Palestinian leaders view technology and implement it in their organizations (Adebayo Olusegun Aderibigbe et al., 2023; Bilokopytova & Karim, 2023; Demaidi, 2023; Shahadat et al., 2023b, 2023a). This is especially relevant as strategic leaders can remove obstacles that hinder innovation implementation and catalyze innovation adoption (Ka, 2023; Kahenda Vita & Muathe, 2023; Özdemir et al., 2020; Rowe, 2001).

Overall, this study focuses on a vital issue and a critical gap affecting the development of technology in the Palestinian context. By investigating the utilities of strategic leadership, perceived innovation attributes, and the relevant context, the study aims to create a comprehensive image of the barriers to and facilitators for AI incorporation. The results of the study may benefit the political economy field and other disciplines and can be used by the stakeholders concerned with the initiation of AI implementation in Palestine.

1.4 Study Objectives and Questions

The main objective of the study is to investigate the influences of information and Communication Technology (ICT) readiness on AI adoption in Palestine, and to examine the moderating roles of strategic leadership and perceived innovation attributes on this relationship. The specific objectives are as follows:

RO1: To investigate the relationship between ICT readiness factors (infrastructure, hardware, information systems, and human resources) and AI adoption in the Palestinian context.

RO2: To examine how strategic leadership moderates the relationship between ICT readiness Factors and AI adoption.

RO3: To explore how strategic leadership role moderates the impact of individual ICT readiness factors on AI adoption.

RO4: To assess how perceived relative advantages of AI influence the relationship between ICT readiness and AI adoption.

RO5: To determine the extent to which the perceived compatibility of AI attributes moderates the effects of ICT readiness factors on AI adoption.

Based on the objectives of this study, the overarching research question is "How do ICT readiness factors influence AI adoption in the Palestinian context, and to what extent do strategic leadership and perceived innovation attributes of AI moderate this relationship?". Specifically, the sub-questions this study aims to answer are as follows:

RQ1: What are the effects of ICT readiness factors (infrastructure, hardware, information systems, human resources) on the level of AI adoption in the Palestinian context?

RQ2: How does strategic leadership influence the relationship between overall ICT readiness and AI adoption in the Palestinian context?

RQ3: In what ways do strategic leadership roles specifically moderate the impact of individual ICT readiness dimensions on AI adoption?

RQ4: How do perceived relative advantages of AI influence the relationship between ICT readiness and AI adoption in the Palestinian context?

RQ5: To what extent does the perceived compatibility of AI attributes moderate the effects of ICT readiness dimensions on AI adoption levels in the Palestinian context?

1.5 Conceptual Framework and Hypotheses

The conceptual model encompasses the following variables: ICT readiness factors (infrastructure, hardware, information systems/software, and human resources), which serve as the independent variables. Strategic leadership and the perceived attributes of innovation (relative advantage and compatibility) are the moderator variables, while Artificial intelligence (AI) adoption is the dependent variable. This relationship is illustrated in the model as follows:

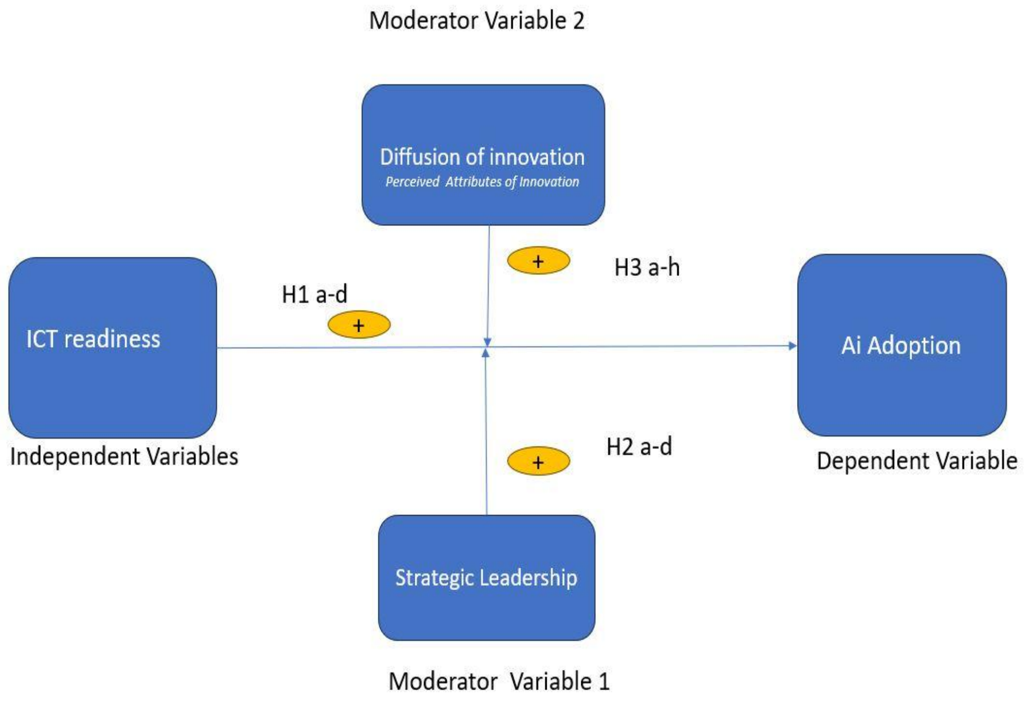

Figure (1.1): Proposed conceptual framework for the study.

1.6 Main Effect Hypotheses

1.6.1 Independent variable (ICT readiness)

H1: ICT readiness factors are positively related to AI adoption.

H1$_a$: The ICT infrastructure factor is positively related to AI adoption.

H1$_b$: The ICT hardware factor is positively related to AI adoption.

H1$_c$: The ICT information system and software factor is positively related to AI adoption.

H1$_d$: ICT people and human resources factor is positively related to AI.

1.6.2 Moderator Variable 1: Strategic Leadership

H2: Strategic Leadership positively moderates the relationship between ICT readiness factors and AI adoption.

H2$_a$: Strategic Leadership positively moderates the relationship between the ICT infrastructure factor and AI adoption.

$H2_b$: Strategic Leadership positively moderates the relationship between the ICT Hardware factor and AI adoption.

$H2_c$: Strategic Leadership positively moderates the relationship between the ICT information system and software factor and AI adoption.

$H2_d$: Strategic Leadership positively moderates the relationship between the people and human resources factor and AI adoption.

1.6.3 Moderator Variables 2 (Perceived attributes of innovation)

H3: Perceived attributes of innovation moderate the relationship Between ICT readiness factors and AI adoption.

$H3_a$: Relative advantage moderates the relationship between the ICT infrastructure factor and AI adoption, such that as the Relative Advantage becomes high, the relationship becomes stronger.

$H3_b$: Relative advantage moderates the relationship between ICT hardware factor and AI adoption, such that as the Relative Advantage becomes high, the relationship becomes stronger.

$H3_c$: Relative advantage moderates the relationship between ICT information/systems factor and AI adoption in the Palestinian context, such that as the Relative Advantage becomes high, the relationship becomes stronger.

$H3_d$: Relative advantage moderates the relationship between ICT people, human resources factors, and AI adoption, such that as the relative advantage becomes high, the relationship becomes stronger.

$H3_e$: Compatibility moderates the relationship between the ICT infrastructure factor and AI adoption, such that as Compatibility becomes high, the relationship becomes stronger.

H3$_f$: Compatibility of the relationship between ICT hardware factor and AI adoption, such that as the Compatibility becomes high, the relationship becomes stronger.

H3$_g$: Compatibility moderates the relationship between ICT information/systems factor and AI adoption, such that Compatibility becomes high, and the relationship becomes stronger.

H3$_h$: Compatibility moderates the relationship between ICT people and human resources factors and AI adoption, such that as Compatibility becomes high, the relationship becomes stronger.

1.7 Study Limitations

Although this research has been designed with care and thought methodology, it has several limitations that must be acknowledged. By recognizing these limitations, one can not only increase the degree of transparency of this research but also help future researchers mitigate those limitations. The primary limitations of this study are as follows:

Scope Limitations: This study is geographically confined to the Palestinian context, implying that the generalizability of the results to other developing economies with distinct socio-economic and political environments may be constrained. Furthermore, the research's sector-specific focus within the Palestinian economy might only encompass some industries, thereby reducing its applicability to specific organizational types or sectors within the region.

Methodological Constraints: This research primarily employs quantitative methods. Several methodological constraints bind the quantitative approach to studying AI adoption in Palestine. One such constraint pertains to the issue of standardized measures, which may not entirely capture the complexity of AI implementation and potentially omit important contextual nuances. Furthermore, the quantitative approach to AI adoption is also complicated by the fact that measures for this phenomenon in developing countries such as Palestine have yet to be established and that the crafting of such measures would require extensive validation efforts to ensure their reliability and validity. The cumulative effect of these constraints showcases that a purely quantitative approach may not accurately capture the complexity of AI adoption and implementation in Palestine.

Resource Constraints: Time resources are among the resource constraints in the ongoing investigation. AI development tends to be fast as new technologies emerge during the research period, and it may be challenging to investigate it in a suitable time frame while ensuring that the study remains relevant at the time of completion. Financial resources limit the amount of data available, as with appropriate funding, it would be possible to increase the sample's size and improve its representativity.

Generalizability of Findings: Several reasons can affect the generalizability of the study's findings. First, Palestine's political and economic situation is unique, which does not allow for generalizing the research results to other developing economies with different challenges. Second, the sample used in the study cannot be highly representative of all organizations in Palestine because the range of organizations differs in their specifications.

Limited literature: The nascent stage of Palestine's AI strategy and the need for more literature on AI adoption in the Palestinian context may restrict the study's theoretical foundation.

1.8 Structural Outline

1.8.1 Chapter One -Introduction

This chapter provides an overview of the study. It starts with the discussions about Artificial Intelligence (AI) adoption and application in the Palestinian context. The chapter continues with a presentation of the research objectives and research questions, the problems, and the purpose of the study. It also justifies the study as the importance of the relationship between ICT readiness factors and AI adoption, focusing on the moderator role of strategic leadership and perceived attributes of innovation, in addition to outlining potential limitations of the study.

1.8.2 Chapter Two -Literature Review

The second chapter gives a review of the literature. It will discuss ICT readiness, strategic leadership, perceived attributes of innovation, and the conceptual model and the hypotheses introduced in Chapter 1.

1.8.3 Chapter Three -Methodology

This chapter will outline the research design and methodology used to explore the interactions among ICT readiness, strategic leadership, perceived attributes of innovation, and AI adoption. It will detail the research approach, data collection methods, and analysis techniques. The chapter will also discuss the rationale for choosing quantitative methods, potential biases, and how these limitations will be addressed.

1.8.4 Chapter Four -Results

Chapter four will present the results of the analyses conducted in the study. It will discuss the main effect hypotheses, which explain how ICT readiness factors influence AI adoption. It will also analyze the moderating effects of strategic leadership and perceived attributes of innovation.

1.8.5 Chapter Five -Discussion and Conclusions

This chapter will give the analysis results against the theoretical framework and the peculiarities of the Palestinian landscape. It will, in addition, explain the issues of the study, give recommendations to practitioners and policymakers, and provide a trajectory for future studies.

1.9 Conceptual Framework

The conceptual framework of this study comprises distinct components aimed at assessing and understanding the interrelationships among ICT readiness factors and both strategic leadership and perceived attributes of innovation as a moderator variable within the context of Palestinian organizations. These components are integral to elucidating the mechanisms through which these variables interact and contribute to the attainment of successful adoption of artificial intelligence.

1.9.1 Conceptual Definitions

Artificial Intelligence (AI) adoption refers to the process by which organizations integrate AI technologies into their operations and business processes. It involves the implementation and utilization of AI systems, algorithms, and tools to enhance productivity, efficiency, and decision-making capabilities (Kurup & Gupta, 2022). AI adoption is characterized by various challenges and factors that influence its successful integration, including technological readiness, organizational culture, employee acceptance, and resource availability (Kurup & Gupta, 2022; Regona et al., 2022)

Information and Communication Technology readiness (ICT readiness): is a broad term used to refer to an organization/country's/region's preparedness to implement ICT-related programs to boost its socio-economic output capacity (Chanyagorn & Kungwannarongkun, 2011). It encompasses the availability and quality of ICT infrastructure, accessibility and proficiency of ICT hardware, the effectiveness of information systems/software, and the technical capacity and administrative capability of the human resources involved in ICT (Chanyagorn & Kungwannarongkun, 2011).

Strategic leadership (SL): Strategic leadership refers to the capacity of top executives to set a clear vision and direction for an organization while aligning its resources and culture with strategic objectives (Boal and Hooijberg, 2001). It encompasses critical decision-making, fostering innovation, and guiding the organization through change while balancing stakeholder needs (Boal and Hooijberg, 2001; Fourie & Jacob Fourie, 2007). Strategic leaders are responsible for establishing ethical practices, developing human capital, and maintaining core competencies, all of which contribute to the organization's long-term success (Mjaku & c, 2020). They must also remain aware of external factors that may impact the organization and adapt strategies, accordingly, ensuring that the organization remains competitive and sustainable in a rapidly evolving environment (Fourie & Jacob Fourie, 2007; Mjaku & c, 2020; O'Shannassy, 2021).

Diffusion of Innovation Theory (DOI): The Diffusion of Innovation Theory, developed by Everett Rogers, is a framework that explains how new ideas, technologies, or practices spread through a social system over time (Nofal & Khalaf, 2021). This theory posits that the adoption of an innovation follows a bell-shaped curve, categorizing adopters into five groups: innovators, early adopters, early majority, late majority, and laggards (Miller, 2015a). The diffusion process is influenced by four main elements: the innovation itself, communication channels, time, and the social system (Miller, 2015b). The theory suggests that the characteristics of innovation, such as its relative advantage, compatibility, complexity, trialability, and observability, play a crucial role in determining its rate of adoption. By understanding these factors and the stages of the adoption process, organizations and change agents can develop more effective strategies for introducing and promoting new ideas or technologies within a given population (Hornor, 2007; Miller, 2015; Rogers et al., 2003).

The perceived attributes of innovation: Defined by the DOI theory is relative advantage, compatibility, complexity, trialability, and observability (Miller, 2015a). Relative advantage gauges the degree to which the innovation is anticipated to enhance the current organizational process. Compatibility assesses the extent of alignment the innovation shares with existing infrastructure, organizational culture, or values (Miller, 2015a). Complexity measures the magnitude or difficulty of understanding and implementing the innovation, while Trialability describes the ease of using and testing the innovation. Lastly, observability encapsulates the level of perception regarding an innovation technique (Hornor, 2007; Miller, 2015a; Rogers et al., 2003).

1.9.2 Operational Definitions

1.9.2.1 Dependent Variable

AI adoption: According to Sadashiv Jadhav (2021a), the study employed a quantitative cross-sectional correlational methodology to analyze the impact of various factors on AI adoption in the SME sector in India. This approach allowed for statistical analysis of relationships between variables. Four indicators will be used to measure AI adoption. A five-point- Likert- scale will be used to assess each indicator from (5) strongly agree to (1) strongly disagree.

1.9.2.2 Independent Variable

ICT readiness: According to Chanyagorn & Kungwannarongkun (2011), the ICT Readiness Assessment Model is recommended for appraising ICT readiness in developing countries and small and medium organizations. The model consists of 15 essential indicators that assess four key ICT factors :(a) ICT infrastructure factor, (b) ICT hardware factor, (c) ICT software and information system factor, and(d) ICT human resources factor. A five-point-Likert- scale will be used to assess each indicator from (5) strongly agree to (1) strongly disagree.

1.9.2.3 Moderating variables

Moderating Variable (1) Strategic Leadership: According to Fourie & Jacob Fourie (2007), the indicators of a strategic leadership role in the organization include (a) determining strategic direction, (b)creating balanced organizational controls, (c) supporting influential organizational culture, (d) highlighting ethical practices, (e) developing and maintaining core competencies, (f) developing human capital, (g) and developing social capital. A five-point-Likert- scale will be used to assess each indicator from (5) strongly agree to (1) strongly disagree.

Moderating Variable (2) Perceived attributes of innovation: According to Sadashiv Jadhav (2021a), The study focused on the dependent variable, the decision of AI adoption (AI-A), and independent variables, including, relative advantage (RA), compatibility (CO), and other independent variables, This methodology and the identified relationships provide insights into the factors influencing AI adoption in SMEs, highlighting the importance of both technological and organizational aspects., The perceived relative advantage attribute with five indicators and compatibility attribute with four will be used to assess each indicator from (5) strongly agree to (1) strongly disagree by five points Likert scale.

Table (1.1) Conceptual and Operational Definitions

Construct	Construct Type	Conceptualization	Operationalization	Source/ Author(s)	Scale
AI adoption	Dependent Variable	The process by which organizations integrate AI technologies into their operations and business processes. It involves the implementation and utilization of AI systems, algorithms, and tools to enhance productivity, efficiency, and decision-making capabilities	4 indicators	(Sadashiv Jadhav, 2021a)	Five-point Likert scale
ICT readiness	Independent Variable	An organization/country's/region's preparedness to implement ICT-related programs to boost its socio-economic output capacity	15 indicators are used under 4 categories including :(a) ICT infrastructure factor, (b) ICT hardware factor, (c) ICT software and information system factor, and(d) ICT human resources factor	(Chanyagorn & Kungwannarongkun, 2011)	Five-point Likert scale
Strategic Leadership	Moderator Variable	The ability of top-level executives to create and execute plans that achieve long-term sustainable success for an organization	7 indicators	(B. Fourie & Jacob Fourie,2007)	Five-point Likert scale
Perceived attributes of innovation	Moderator Variable	Refer to how potential adopters view certain characteristics of a new idea or technology, which influence its adoption rate	11 indicators are distributed based on 2 dimensions, which are: (a) Relative advantage, (b) Compatibility	(Sadashiv Jadhav, 2021a)	Five-point Likert scale

Chapter Two

Theoretical Framework

2.1 Introduction

This chapter synthesizes existing research, theoretical insights, and empirical evidence to develop a comprehensive understanding of the relationship between ICT readiness, strategic leadership, perceived innovation attributes, and their collective influence on AI adoption in Palestine. The chapter identifies research gaps through a systematic review of literature, enabling the study to offer a novel perspective on AI adoption. It presents various ICT readiness factors, such as infrastructure, hardware, information systems, and human resources, emphasizing the critical role of strategic leadership and innovation attributes in identifying the main barriers and/or drivers of AI adoption.

2.2 Conceptual Foundation

2.2.1 ICT Readiness

Information and Communications Technology (ICT) readiness is a term that refers to an organization’s ability to manage and use technology, including hardware, software, information systems, infrastructure, and human resources (Abu Mansour, 2022; Chanyagorn & Kungwannarongkun, 2011; Mukhametov, 2022). This form of preparedness reveals the extent to which these corporations are willing to accept new technologies and utilize them with respect to their objectives (Chanyagorn & Kungwannarongkun, 2011). It is seen in terms of advanced technologies being used even by large companies to enhance competitiveness and facilitate innovation (Huggins et al., 2022), and organizational efficiency (Mo, 1012b). Across a wide range of businesses, ICT has emerged as a crucial element of worldwide organizational operations (Frangos, 2022; Shahadat et al., 2023b). It consists of an extensive array of technology resources and techniques that facilitate effective communication, management, storage, and distribution of information inside businesses (Blurton, 1999b). Colby & Parasuraman (2001) emphasize that technological readiness is more than just a measure of one's ability to use technology; it is also an assessment of individuals' perceptions and attitudes toward technology use.

While various ICT readiness assessment tools have been developed and used by organizations, their applicability to small and medium-sized enterprises (SMEs), particularly in developing countries, is limited (Abu Mansour, 2022; Chanyagorn & Kungwannarongkun, 2011). E-readiness assessment tools and models provide valuable insights for multinational corporations looking to invest in technologically innovative countries and tailor their digital strategies accordingly (Blurton, 1999b; Chanyagorn & Kungwannarongkun, 2011; Unit, 2012). Statistical techniques like Principal Component Analysis (PCA) are used to streamline the assessment process and make it more applicable to SMEs, particularly in developing countries. PCA helps identify important ICT development indicators for the creation of a new set of indicators tailored to the requirements of small and medium-sized enterprises (Fathian et al., 2008).

ICT readiness involves a bunch of fundamental elements that play the part of a beacon in determining the strength of technology taking off, especially amid cutting-edge technologies like AI (Iaia et al., 2024). The study on the ICT Readiness Valuation Model Chanyagorn & Kungwannarongkun (2011) builds upon this foundation. It offers a structured framework that assesses the ICT readiness in developing countries and organizations with smaller sizes. This model evaluates four main ICT factors: infrastructure details, information technology, hardware, and human resources provided by 15 key performance indicators (see Figure 2.1). The first essential element of ICT readiness factors is the ICT infrastructure factor, which is digital organizational operations or the foundations upon which they operate (Chanyagorn &

Kungwannarongkun, 2011; Mukhametov, 2022). This involves a set of fundamental technologies and services that underpin cloud computing services, data centers, networking devices, etc. This provides the requisite support for the deployment and functioning of AI systems in organizations (M. Chen et al., 2013).

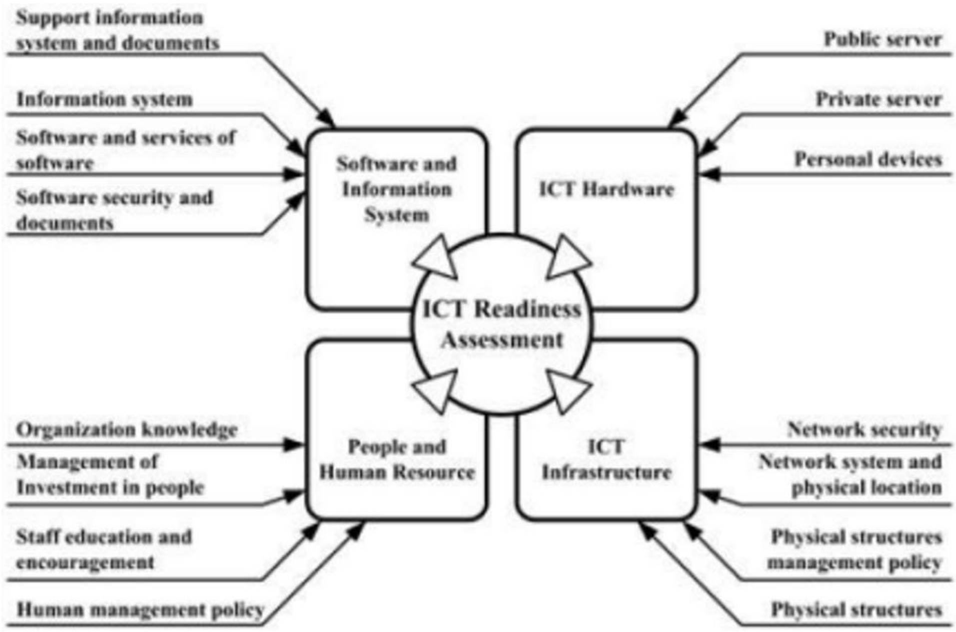

Figure (2.1): ICT Readiness Assessment Model with new indicators for small and medium-scale enterprises. Source (Chanyagorn & Kungwannarongkun, 2011).

Second, ICT hardware includes physical devices such as computers, servers, networking devices, and storage devices. The hardware must be capable of supporting the computational demands of AI, which often require high processing power and large storage capacities (MWAPWELE et al., 2019; Zebec & Indihar Štemberger, 2020)

Third, Information Systems and Software are the applications and programs that process and manage data. They include databases, enterprise resource planning systems, customer relationship management systems, and AI software itself. The readiness of these systems and software can significantly influence the adoption of AI (Rawashdeh et al., 2023; Salleh et al., 2023).

The company's adaptability to AI is determined by the way that these technologies are utilized and are available, which leads to the fourth factor of ICT readiness, People and Human

Resources, which have an immense role in innovative technology incorporation initiatives (Budhwar et al., 2022; Pathak & Solanki, 2021). The workforce must have the necessary expertise, including knowledge and skills, to use and oversee human capital prudently. In addition to the technical aspects of AI, employees must get training on AI applications that they can use in real-time commercial projects. This will help them become more practical and skilled at solving problems (Budhwar et al., 2022; Pathak & Solanki, 2021).

2.2.2 Artificial Intelligence

The journey of AI began with pioneers like Allen Newell and Herbert Simon, who introduced the concept at the Dartmouth Conference in 1956, setting off a chain of developments that led to significant milestones such as the creation of WABOT-1, the first robot in Japan in 1972 (Mansilla, 2020). AI's further development before 2000 was limited by the lack of funding; computers were not as powerful as they are presently and could not store substantial data. For the last 15 to 20 years, progress in computer processing and storing abilities has reduced all the barriers to AI research and empowered a new reality where AI applications are integral to the functioning of society (Mansilla, 2020).

Therefore, Artificial Intelligence has evolved from its simple conception in the 20th century to its current form as a system capable of learning, decision-making, and mimicking human intelligence. Artificial intelligence was developed with key milestones that shaped its path, such as the chess-play computer that underwent the early stages of AI (Chi et al., 2020). Following the increased speed of computer processing, AI expanded as well as ways for its integration into various disciplines and business sectors, evolving in different ways that have transformed industries through automation of tasks, complex data analysis, and predictive strategies (Arora et al., 2021; Mansilla, 2020; Stix, 2022).

There are three main types of AI. The first type is Narrow AI or Artificial Narrow Intelligence (ANI), which is artificial intelligence limited to a narrow task (e.g., facial recognition or internet searches) without understanding the broader scope of human intelligence (Bilokopytova & Karim, 2023; Böhmer & Schinnenburg, 2023a; Chang, 2022; Macdonald et al., 2023; Stix, 2022) .This includes several applications across different sectors. For example, Expert Systems that are used for decision-support systems and data analysis applications that significantly improve efficiency in sectors like pharmaceutical and finance (Chang, 2022). For example, IBM's Watson offers cancer diagnosis and prescribing recommendations (Macdonald et al., 2023). In a similar line, Robotic Process Automation (RPA) is used in finance to automate highly repetitive tasks and data processes, enabling staff to focus on high-value work. Leading firms such as UiPath and Automation Anywhere develop automation tools that companies use for transaction processing automation in finance and onboarding new employees in HR (Böhmer & Schinnenburg, 2023a). Third, Natural Language Processing (NLP) is used in search algorithms, such as for 'Arab' companies like Souq.com – now Amazon. Ae – to chat with customers to enhance user interaction (Macdonald et al., 2023). Finally, Image processing, such as in medical imaging equipment, autonomous vehicles, and safe city systems, can monitor video feed traffic systems and security (Khan et al., 2022; Qian et al., 2024). Arab countries, especially in the Gulf, are investing in smart cities, incorporating technology to manage traffic systems and implement security measures (Bilokopytova & Karim, 2023).

The second type of artificial intelligence is Artificial General Intelligence (AGI), which refers to AI systems that possess the ability to understand, learn, and apply intelligence across a wide range of tasks, akin to human intelligence (Alqarni et al., 2023; Latif et al., 2023). While AGI remains theoretical mainly, its potential applications could revolutionize every aspect of human life, from personalized education to comprehensive healthcare solutions(Latif et al., 2023). The development of AGI would mark a significant milestone in achieving systems that can perform any intellectual task that a human being can do. However, as of now, no AGI systems have been successfully developed (Alqarni et al., 2023; Latif et al., 2023). The third type is Superintelligent AI (ASI), which refers to an AI that surpasses human intelligence across all fields, including creativity, general wisdom, and problem-solving (Pranjali Amalkar, 2023). The implications of ASI are profound, potentially leading to breakthroughs in science, medicine, and technology. However, ASI also poses ethical and safety concerns, as its capabilities could outstrip human control (Pranjali Amalkar, 2023). Theoretical discussions around ASI often revolve around ensuring that such intelligence aligns with human values and goals (Pranjali Amalkar, 2023).

The importance of AI across these types and functions cannot be overstated. Each type of AI has found applications across different sectors, revolutionizing industries by enhancing efficiency, decision-making, and innovation (Chi et al., 2020). For instance, AI is used in the agriculture sector to rationalize the area under cultivation. In addition, AI, including the use of machine learning, is popular in the agriculture sector, and this has been discussed in the AI & Ml Based Advising System for Farmers Crop Production report ("Ai & Ml Based Advising System for Farmers Crop Production," 2020). In the athletic apparel and footwear industry, companies like NIKE Inc and Addidas Inc. are leveraging AI for digital transformation, utilizing technologies such as the Internet of Things (IoT) and Big Data to enhance operational efficiency and competitiveness (Puterisari, 2022) . The water sector also benefits from AI-supported resource management, through which smart irrigation systems ensure more efficient water use by forecasting the weather and monitoring soil moisture levels (Obaideen et al., 2022). The use of AI in the environmental sector is demonstrated by the study that reviews air pollution monitoring using AI and concludes that such tools offer a creative way of addressing environmental challenges by enabling much more dynamic and variable ways of monitoring and combating pollution (Tiwari et al., 2023). AI-supported tutoring systems are also used in education, which improves the effectiveness of learning, as shown in the studies of such technologies (Digesh, 2023; Xu et al., 2021). Transportation is another sector that benefits from the use of AI, which is used to optimize routes and develop unmanned ground vehicles. Transportation experts show optimistic expectations about AI assumptions as mechanisms for improving efficiency, cutting costs, and enhancing the quality of the traveler experience (Nayif Alahmadi, 2020). In finance, AI applications in satellite imagery and data are support the enforcement of Environmental, Social, and Governance goals, showcasing how financial technology can aid in achieving sustainable finance (Z. Yang & Broby, 2020). Healthcare has seen remarkable advancements with AI diagnosing diseases with unprecedented accuracy, highlighting the technology's potential to revolutionize medical diagnostics and treatment (Corrales-Hernández et al., 2023).

Internationally and in the Arab world, companies leveraging AI are not only achieving greater operational efficiency (Almarzooqi, 2019; Jasimuddin et al., 2017). However, they are also driving innovation, creating new business models, and offering enhanced services and products (Al-Ammary & Ghanem, 2024; Almarzooqi, 2019; Huq et al., 2019; Jasimuddin et al., 2017). The integration of AI into various sectors underscores its transformative potential, highlighting the importance of continued investment in AI research and development to harness its full capabilities for societal benefit (Bilokopytova & Karim, 2023; Böhmer & Schinnenburg, 2023b)

The adoption and implementation of artificial intelligence in Palestine present an enormous potential for economic and institutional expansion in light of the challenging region’s political, social, and economic conditions (Musleh, 2022; Raddad & Samat, 2016; Tadj et al., 2023). Potentialities for AI applicability cut across various sectors, such as education, health, and water management, which are plagued by factors like strikes, rare resources, and monopolization of resources by Israel (ESCWA, 2022; Musleh, 2022; Raddad & Samat, 2016; Tadj et al., 2023). In the education sector, AI has the potential for a “digital revolution” by facilitating personalized education programs and ensuring learners access to more information and knowledge, even during the closure times of schools and universities. In this regard, the education process becomes more attuned to individual learners, thereby cushioning them against external disruption (Abdelmoneim et al., 2024; ESCWA, 2022). In relation to AI usage for educational activities, the reflections of the Gaza Strip’s teachers can be described as cautiously optimistic, noting the pertinent challenges. Teachers indicate the increased possibility of AI usage for teaching and learning while still expressing concerns about being able to implement this method effectively (Abdelmoneim et al., 2024). In the health sector, the implications can substantially be beneficial for patients and doctors by optimizing resource allocation, bettering diagnosis, and ensuring patients’ remote monitoring, thus affording the resource-scarce context milestone achievements (ESCWA, 2022; Hasan et al., 2024; Mosleh et al., 2023). These studies suggest that the application of AI in this sector presents enormous potential, but there is a need to enhance practitioners’ knowledge of the use of this method (ESCWA, 2022; Hasan et al., 2024; Mosleh et al., 2023).

The economic implications of AI in Palestine are closely related to broader technological and regulatory trends. For example, the study on Morphogenetic Régulation describes AI’s impact on the political economy and the internet’s infrastructure, hence, the influence on economic processes and governance in Palestine, in general (Dryhurst et al., 2023). Another sector that will benefit from AI is agriculture, and specifically water management. AI and Internet of Things solutions can help optimize the use of irrigation and desalination for sustainable agriculture in Palestine (ESCWA, 2022; H. & Veeramanju, 2023; Istaitih & Mencet, 2014) .

2.2.3 Strategic leadership

Boal and Hooijberg (2001:517) posited that the responsibilities of leaders in top management positions are often linked with strategic leadership endeavors such as strategic decision-making, instilling ethical value systems into an organization's culture, fostering that effective organizational climate, and "creating and communicating a vision of the future; developing key competencies and capabilities; developing organizational structures, processes, and controls; managing multiple constituencies; selecting and developing the next generation of leaders". In line with this, Lussier (2016: 396-400) emphasized the centrality of strategic leadership to an organization's capacity to "adapt, evolve, and prevail amid turbulent disruptions" (p. 396) and to "identify relevant environmental factors and industry drivers that weigh on the organization's vision, mission, objectives, strategy, and business models" (Lussier, 2016, p. 400).

For the purpose of this study, strategic leadership is defined as a manager's capacity to "anticipate, envision, maintain flexibility, think strategically, and work with others to initiate changes that will create a viable future for the organization" (Lussier, 2016, p. 477). Most importantly, Quong and Walker (2010a) stated, "When leaders are engaged in the management processes of analyzing, planning, implementing, monitoring and evaluating, they were basically considered to be strategic" (p. 22). Strategic leadership accentuates how leaders choose the tactics to meet those objectives by making significant decisions that impact the overall performance, achieving a sustainable competitive advantage, and the future welfare of the organization (Mahdi & Almsafir, 2014a; Nicole Paisley et al., 2018).

Strategic leadership plays a pivotal role in driving technology advancement and AI adoption within organizations. It provides the vision, direction, and framework necessary for the successful integration of new technologies and AI systems (Hussain & Rizwan, 2024). Strategic leaders are responsible for raising awareness, securing commitment, and allocating resources for technological initiatives (Hussain & Rizwan, 2024; Tarisayi, 2024). They guide the organization through a phased approach to AI adoption, starting with low-cost, general-purpose tools and progressing to more advanced, customized solutions (Hussain & Rizwan, 2024; Tarisayi, 2024). Strategic leadership also involves developing core competencies crucial for effective digital leadership, including technological acumen, adaptability, and ethical considerations (Shahzad, 2024). In the context of AI adoption, strategic leaders must navigate the complex interplay between utilitarian and hedonic values, addressing factors such as perceived usefulness, ease of use, and enjoyment (Gupta & Yang, 2024). Furthermore, strategic agility, fostered by effective leadership, enables organizations to achieve sustainable competitive advantage in rapidly evolving technological landscapes (Hussain & Rizwan, 2024; Rizki et al., 2023). By aligning technological initiatives with organizational goals, addressing barriers to adoption, and fostering a culture of innovation, strategic leadership is instrumental in ensuring the successful advancement and integration of technology and AI within organizations (Tarisayi, 2024).

2.2.4 Diffusion of Innovation

The Diffusion of Innovation Theory (DOI), developed by Everett Rogers 1962, is a framework that explains how new ideas, technologies, or practices spread through a social system over time (Nofal & Khalaf, 2021). This theory posits that the adoption of an innovation follows a bell-shaped curve, categorizing adopters into five groups: innovators, early adopters, early majority, late majority, and laggards (Miller, 2015a). The diffusion process is influenced by four main elements: innovation itself, communication channels, time, and the social system (Miller, 2015a). The theory suggests that the characteristics of innovation, such as its relative advantage, compatibility, complexity, trialability, and observability, play a crucial role in determining its rate of adoption. By understanding these factors and the stages of the adoption process, organizations and change agents can develop more effective strategies for introducing and promoting new ideas or technologies within a given population (Hornor, 2007; Miller, 2015a; Rogers et al., 2003).

Relative advantage gauges the degree to which the innovation is anticipated to enhance the current organizational process (Miller, 2015a; Rogers et al., 2003). Compatibility assesses the extent of alignment the innovation shares with existing infrastructure, organizational culture, or values (Miller, 2015a). Complexity measures the magnitude or difficulty of understanding and implementing innovation, while Trialability describes the ease of using and testing the innovation (Rogers et al., 2003). Lastly, observability encapsulates the level of perception regarding an innovation technique (Hornor, 2007; Miller, 2015; Rogers et al., 2003).The importance of this theory lies in providing a conceptual framework to understand how digitalization can be integrated into corporate environments (Chatterjee, Rana, et al., 2021). It explains the mechanisms by which innovations spread through social networks during communication processes, highlighting that innovation is a broad term encompassing all types of technological advancements (Miller, 2015). This perspective helps identify the social factors and communication patterns that influence the adoption and dissemination of digital technologies, offering valuable insights for managing digital transformation in organizations(Chatterjee, Rana, et al., 2021). It identifies how innovations spread through social networks in communication processes and states that innovation is a generic term for all technological innovations (Miller, 2015a).

Additionally, this theory of innovation adoption is frequently compared with models like the Technology Acceptance Model (TAM) and the Unified Theory of Acceptance and Use of Technology (UTAUT). In one way, TAM and UTAUT are concerned with people’s judgment on information technology (Chatterjee, Rana, et al., 2021; Tasić, 2018). However, DOI pays attention to the broader social context during which the progress of that kind of technology is inevitable (Miller, 2015a). The DOI framework proposes intra-organizational innovativeness as the vital factor, which is described as the early adoption of innovation compared to competitors (Vagnani et al., 2019).

In conclusion, this framework explains how, why, and at what pace new ideas and technologies permeate cultures (Miller, 2015; Usman et al., 2019). When applied to artificial intelligence (AI), it provides critical insights into the factors driving AI adoption and implementation across various sectors (Baytak, 2023; Cao et al., 2021; Higham et al., 2023). The framework also distinguishes key innovation characteristics that will guide the current study, which aims to identify the factors influencing AI adoption in Palestine. The research will focus on examining the relative advantages and compatibility of AI, offering more profound insights into the dynamics of technology adoption in organizational contexts.

2.3 Theory building and hypotheses development

2.3.1 ICT readiness and AI adoption

Robust ICT infrastructure is critical for the efficient deployment of AI technologies. According to the research studies, there is a close connection between ICT public acceptance and adoption of new technologies, which correlates with ICT readiness variables such as ICT infrastructures, hardware systems, information systems/software, and human resources (Alsheibani et al., 2018; Chanyagorn & Kungwannarongkun, 2011; Gao & Liu, 2023; Martínez-Plumed et al., 2021). Moreover, there is another aspect that is systematically connected to the underlying skills in information technology: namely, a tendency to adopt new tools is remarkably more frequent in such individuals (Chanyagorn & Kungwannarongkun, 2011; Shonubi, 2023).

In the field of Communication Management, Zerfass et al. (2020) shed light on the challenges that professionals face despite their limited knowledge of AI. Their study is based on the TOE framework (Technology-Organization-Environment), which is a model that examines the factors influencing an organization's adoption of technological innovations by considering the interplay of technological, organizational, and environmental contexts (Zerfass et al., 2020). Their study emphasized macro-level variables such as industry structure and communication processes. They discovered a need for clarity in roles and responsibilities with AI technology, indicating deficiencies in Information Technology and Management Support (Zerfass et al., 2020).

Savola et al. (2018) stated that AI is used in marketing management by small and medium businesses in Finland and Sweden. They differentiated AI-powered marketing management systems in terms of their ability to persuade users and examined influencing factors using The TOE and TAM (Technology acceptance model) conceptual frameworks. Marketing management of SMEs often suffers from the adoption of AI, and several reasons have been pointed out, involving these six factors: compatibility, management support, business volume, market pressure, and norms.

Mahroof (2019) explored the isolated automation components, like integrated AI in inventory management and digital storage, that large retailers use. According to the research, the organizational management was not able to support the implementation of AI management and data information technology as the other barriers failed to make AI successful. It was implemented through the suitable UTAUT and TOE models, which are the frameworks for making the proper decisions based on technology. Pumplun et al. (2019b) highlighted an organization's readiness for AI implementation in the context of Germany and Ireland through the model of the TOE framework. Their study showed them if there was a visible trend in migrating major companies from one country to another or if there was an issue with data protection and regulations such as the GDPR (General Data Protection Regulation), which is a comprehensive data privacy law enacted by the European Union (Pumplun et al., 2019b). Other findings have pinpointed organizational slack as a critical aspect of mitigating AI talent shortage problems, as mentioned in Alsheibani et al. (2018). Also, management support was a core component of their recommendations for AI application scenarios in the SMEs of Australia. Perhaps the quickest way to leave the AI application barriers is to help more people have a clear mindset by sharing knowledge about AI within the corporate sector (Alsheibani et al., 2018).

Almaimouni et al. (2014) conducted an exhaustive study on the complicated relationship between societal effects and e-commerce adoption among micro and small Saudi firms. They offered clarifications on the multitude of ways in which stakeholders' and business owners` perceptions and opinions influence their decision-making regarding the application of e-commerce technology. The outcomes of their research also revealed that the social background in which e-commerce activities exist needs to be understood, as well as the customization of approaches used for social impacts.

Rahayu & Day (2015) appraised the multitude of factors that influence the dissemination of e-commerce among Indonesian businesspeople. It highlighted the fact that the innovation readiness of an organization is one of the most crucial factors for the success of technology implementation. In addition, they showed that those internal capabilities and managerial expertise are the keys to implementing e-commerce in the right way. In addition, they noted the inconsistent features of organizational reactions to technological initiatives. They listed innovation and perceived advantages as the two key determinants that factor in the adoption and use of e-commerce platforms.

In their comprehensive study on the adoption of e-commerce by SMEs in Kuwait, Al-Alawi & Al-Ali (2015) pointed to a variety of sophisticated factors that influence organizational decisions in this domain. The study mentioned above stressed senior management's contribution to SME integration of technological systems. They underscored the critical importance of institutional context support for e-commerce growth along with the influence of legislative and policy frameworks in the adoption landscape.

In order to survive in today's world, businesses must prosper and progress in various stages of AI adoption. Business readiness accounts for the organizations' ability and willingness to implement new technologies (Govori & Sejdija, 2023; Ransbotham et al., 2018). At the same time maturity describes the more sophisticated management concerns that are related to the organizational level of technology, whereas technology use goes beyond the adoption of established practices (Mittal et al., 2012). The Capability Maturity Model (CMM) provides insights into organizational maturity, particularly in managing software development processes, and is divided into five levels: initial, repeatable, defined, managed, and optimizing, illustrating the transition from ad hoc system production to quality-controlled processes (Lacerda & von Wangenheim, 2018).

Recent studies have pointed out the contribution of maturity and readiness views on the organization of AI in the business sector. Sadiq et al. (2021) observed that 15 AI recently presented maturity models (AIMM) had gone through only half of the rigorous validations, making them particular cases that have been created to deal with specific issues. Further, most of them were focused on business and process scopes. Hence, there are studies on the performance of project maturity and readiness at the process level in industries that should be conducted. However, this model is distinct for self-assessment of maturity or improvement, as is the case with most AI maturity models. On the other hand, aligning the readiness criterion of the research with that of project teams to observe the extent of changing strategy based on the readiness or maturity level of the technology was also considered (Alsheibani et al., 2018; B. Kim et al., 2020)

To effectively integrate the readiness concept, a metric was needed to track project progress toward operational deployment. The Technology Readiness Levels (TRL) scale, which NASA created, is used to track technologies from preliminary scientific research through to practical applications (Martínez-Plumed et al., 2021). TRL has nine levels with these scenarios that are appropriate for different environments. A diversity of technological applications can be catered to using TRL, including intelligent systems. Furthermore, Martínez-Plumed validated the scale's relevance to AI adoption by assessing AI technologies (Martínez-Plumed et al., 2021).

Comprehensive studies into the issue of AI adoption have been done, which have all the components of AI adoption, which include organizational support and regulation to ensure AI application across various sectors is done the right way (Bankins, 2021; Cao et al., 2021; Pumplun et al., 2019b). At present, the long-standing gap or a paradigm shift between rich and developing countries is no longer in existence as a result of the change in the way ICT is used (Adebayo Olusegun Aderibigbe et al., 2023; Demaidi, 2023) Alternatively, it is becoming clear that an advanced technology sour question necessitates a holistic strategy that forms the unity of the ICT ecosystem constituents (Demaidi, 2023; Treacy, 2022). The result of this shift in perspective should be understood regarding Palestine since disseminating state-of-the-art ICT innovations requires the examination and enhancement of ICT preparedness in many aspects, including but not limited to hardware, infrastructure, software, and human resources (Chanyagorn & Kungwannarongkun, 2011; ESCWA, 2022; Morrar et al., 2019)

This can be achieved through developing a comprehensive strategy that transcends just technological innovations (Demaidi, 2023; ESCWA, 2022; Madan & Yadav, 2016; Solomon Nsor-Anabiah et al., 2019). This entails the establishment of groundbreaking, pioneering projects, judicious utilization of human resources, and the enactment of flexible legislation that can suit technology users' needs, enhance performance overall, and realize its dream of sustainable development.

Based on the preceding discussion, the following hypotheses are developed to correspond to the four elements of ICT readiness. The primary hypothesis (H1) posits that ICT readiness factors are positively related to AI adoption in the Palestinian context. This hypothesis is further broken down into four sub-hypotheses focusing on specific aspects of ICT readiness:

H1: *ICT readiness factors are positively related to AI adoption.*

2.3.2 ICT Infrastructure and AI Adoption

ICT Infrastructure refers to the technical and service facilities required for an organization to function as a virtual and interactive entity (Blurton, 1999a; Chatterjee, Chaudhuri, et al., 2021; Mukhametov, 2022). Key components like cloud platforms, data centers, and networking equipment form the foundation for AI applications, creating the necessary digital (Chanyagorn & Kungwannarongkun, 2011; Chen MIN et al., 2013; Zebec & Indihar Štemberger, 2020). The hypothesis suggests a direct correlation between the quality of ICT infrastructure and the success of AI adoption, specifically within Palestine's socio-political context.

This review examines different aspects of ICT infrastructure, such as physical structures, network systems, and security, and how they influence AI adoption. Various studies highlight that robust ICT infrastructure enhances the likelihood of successfully implementing AI technologies (Demaidi, 2023; Markaki et al., 2023; Martínez-Plumed et al., 2021). For example, research in Palestine’s online banking sector showed that factors like performance expectancy and facilitating conditions, supported by ICT infrastructure, influence consumer attitudes toward AI adoption (Salem & Rassouli, 2024). A reliable ICT infrastructure also strengthens trust in financial institutions, further promoting the acceptance of AI technologies (Salem & Rassouli, 2024).

Similarly, investors' willingness to adopt e-government services in Zanzibar, a comparable developmental context, depended significantly upon the availability of ICT infrastructure, including human capital and affordability (Mussa Ali et al., 2023). Furthermore, ICT infrastructure, internet skills, and social influence were among the vital determinants of Kenyan universities' adoption of open-access scholarly publishing technology, indicating a similar trend that could be applicable to the Palestinian academic sector (Waithaka et al., 2022). The use of AI, including the Industrial Internet of Things in industrial applications, is another example. It highlights the importance of adequate ICT infrastructure for managing security hazards and implementation effectiveness (Alotaibi, 2023). Additionally, Network security is a critical component of ICT infrastructure that affects AI adoption(Gulia et al., 2022; Md. T. Islam et al., 2023). The inherent risks associated with AI systems, especially in network-sensitive applications like intrusion detection systems, highlight the need for advanced security measures (Md. T. Islam et al., 2023; Senevirathna et al., 2024). In addition to safeguarding the integrity of data, adequate network security helps to instill the confidence necessary for people to use new technologies (Alotaibi, 2023; Md. T. Islam et al., 2023). Several studies have identified specific indicators of ICT infrastructure that influence technology adoption (Czarnul & Matuszek, 2019; Mukhametov, 2022). These include internet penetration, broadband connectivity, wireless infrastructure, and the availability of required hardware (Akinola, 2023; Bessadok et al., 2018; Nour, 2016; Nusir et al., 2023). The advent of 3G and 4G networks has significantly increased internet access and mobile web browsing, leading to a more user-centric and mobile internet e (Akinola, 2023; Bessadok et al., 2018; Nour, 2016; Nusir et al., 2023). This increased connectivity has facilitated the adoption of new technologies, including AI (Akinola, 2023; Bessadok et al., 2018; Nour, 2016; Nusir et al., 2023). Finally, the area where ICT preparedness cannot be overlooked is wireless infrastructure as well. Wireless and communication-related infrastructure has brought about an increase in the number of smart mobile devices having internet connection capabilities with much ease (Nour, 2016; Obaideen et al., 2022; Pillai et al., 2021). Technology adoption is significantly dependent on the availability of necessary gear, such as computers and smart devices (Nour, 2016; Obaideen et al., 2022; Pillai et al., 2021).

However, despite the above, several barriers may hinder the adoption of superior technologies (Nandhini et al., 2022a; Ogunrinade et al., 2020). According to (Ogunrinade et al., 2020), they include the high prices for computer gear and software, insufficient infrastructure, a lack of human skills and expertise in ICT, and a need for more relevant software. Such barriers can hinder the adoption of new technology as well as failing to realize the potential benefits of the ICT infrastructure. For instance, the lack of internet access in particular territories in Palestine may affect AI use (Nandhini et al., 2022a; Nour, 2016; Shahadat et al., 2023b; Tabar et al., 2021) However, based on the literature reviewed and the research above, it can be hypothesized that the use of AI in Palestine will have a positive correlation with higher ICT infrastructure levels. This is evident because a sound ICT infrastructure serves as a ground for the mobilization of new technologies.

H1$_a$: *The ICT infrastructure factor is positively related to AI adoption.*

2.3.3 ICT hardware and AI adoption

ICT hardware encompasses all the concrete pieces of equipment and instruments that are necessary to run and maintain AI (Hoffmann & Nurski, 2021). Computers, servers, networking, and storage devices are just a few instances of these (Blurton, 1999a; Mukhametov, 2022; Nandhini et al., 2022a). The study carried out by MWAPWELE et al. (2019) shows the need for hardware that will be able to support the computational demands of AI machines. The adaptation of innovative technologies, such as AI, is very much influenced by the possession of ICT hardware tools, like servers, universal serial bus controllers, personal computers, and processors with AI capabilities (Blurton, 1999a; Martínez-Plumed et al., 2021; Mukhametov, 2022; Nandhini et al., 2022a).

Several studies have examined the impact of ICT hardware on technology adoption. For instance, a study conducted in Nigeria found that the high cost of computer hardware and software, along with the lack of adequate funds and internet facilities, were significant obstacles to the adoption of ICT in secondary education (George, 2006). Similarly, a study in Iraq identified the availability and affordability of hardware and software, ICT support services, and network reliability as crucial factors influencing the adoption of e-health services in Iraqi hospitals (Ali et al., 2023)

Additionally, Private servers are critical for internal data processing and storage, which are essential for AI applications. The use of edge AI platforms, which perform data analysis directly on devices, reduces latency and enhances data privacy (R. Kim et al., 2023). This is particularly relevant in sectors like healthcare and finance, where data sensitivity is paramount (Adams et al., 2023; Ali et al., 2023; Sun & Medaglia, 2019; Z. Yang & Broby, 2019).

Similarly, Public servers facilitate external data processing and service provision (Abu Mansour, 2022; Chanyagorn & Kungwannarongkun, 2011; Ramirez-Madrid et al., 2022). The EXPERIENCE project, which uses explainable AI and VR to create personalized environments, relies heavily on public server infrastructure to manage and process large volumes of data and allows the public at large to create their own VR environments automatically through portable devices (e.g., smartphones/tablets) without the need for technical skills (Valenza et al., 2023). This infrastructure is more developed in advanced economies, supporting a higher rate of AI adoption (Fathalla Salama, 2024; Valenza et al., 2024).

A study on the adoption of Industry 4.0 technology within the kiwifruit industry in New Zealand highlighted the importance of robust ICT hardware, including sensing, image recognition, and robotics hardware, for successful technology adoption (Pickering et al., 2023). The adoption of AI in Palestine is closely tied to the availability of essential ICT hardware, such as personal devices, public servers, and private servers. However, the limited availability of this business-specific hardware can hinder the application of AI technologies (Abu Mansour, 2022; Chanyagorn & Kungwannarongkun, 2011; Demaidi, 2023; ESCWA, 2022; Madan & Yadav, 2016; Solomon Nsor-Anabiah et al., 2019).

Consequently, Research suggests that as ICT hardware infrastructure improves, AI usage is likely to increase, aligning with the proposed conceptual model that highlights a positive relationship between the two. In conclusion, it can be hypothesized that the use of AI in Palestine will have a positive correlation with higher ICT hardware levels.

H1$_b$: *The ICT hardware factor is positively related to AI adoption.*

2.3.4 ICT Information System/Software and AI adoption

The availability and quality of information systems infrastructure play a significant role in the adoption of advanced technologies such as AI. This is particularly true in the context of software, databases, and information technology, which have been found to significantly influence the effectiveness of information systems (Zebua et al., 2022)

At the same time, databases are required to process and store the vast amounts of information necessary for the proper training and functioning of AI systems(Bisola Beatrice Oguejiofor et al., 2023; Roh et al., 2019a). In the case of any omissions or low quality of the database, the AI system's performance will also be low. Thus, databases also have a significant impact on AI technologies (Zebua et al., 2022). Information technology, including the hardware and networking infrastructure, also plays a critical role (Al-Ammary & Ghanem, 2024; Almaiah, Alhumaid, et al., 2022; Gebreegziabher, 2020). A robust IT infrastructure can support the high computational demands of AI technologies and facilitate the efficient transmission and processing of data (Zebua et al., 2022).Security is another critical aspect of information systems that can impact AI adoption. As AI technologies often involve the processing of sensitive data, robust security protocols are necessary to protect this data and maintain user trust (Seniv et al., 2023). However, increasing the availability of AI-compatible information systems and data-centric software could positively influence the ability to implement AI solutions (Zebua et al., 2022). In the context of Palestine, the limited availability of compatible systems and relevant data may indeed hinder AI adoption (Demaidi, 2023; ESCWA, 2022; Tadj et al., 2023)

Based on these findings, we can provide preliminary support to a sub-hypothesis that states that the higher the levels of compatible information systems and AI-relevant software in Palestine, the more AI technologies would be implemented. This is supported by the literature review of the effect of information systems on innovation adoption.

H1$_c$: *The ICT information system and software factor is positively related to AI adoption.*

2.3.5 ICT people /Human Resources and AI adoption

Human capital, a critical factor for ICT readiness, which includes individuals' technical abilities, AI knowledge, STEM education, and digital literacy, significantly influences the receptiveness to and innovation of technology (Salam et al., 2019). Investments in human capital growth can drive technological advancements (Gerhart & Feng, 2021; Marius Martin et al., 2011). For small and medium enterprises, staff expertise is essential for success and expansion (Marius Martin et al., 2011), and a shortage of trained personnel can hinder the adoption of technologies like AI (Gaur et al., 2021; Marius Martin et al., 2011; Twan, 2023).

Effective human resource management (HRM) policies, such as those encouraging staff development and continuous learning, are crucial for promoting AI adoption (Alassaf et al., 2020; Xiang et al., 2023). Studies have shown that organizational policies supporting professional development and skill-building are significant predictors of AI adoption (Ahmić, 2023; M. Islam et al., 2022). For example, Cooke et al. (2022) highlighted the importance of human-centered AI practices in building workforces capable of adapting to technological changes.

Proper management of investments in human capital is the first step in successfully integrating AI systems (Marius Martin et al., 2011; Twan, 2023). Organizations that foster knowledge management and employee expertise create a strong foundation for AI implementation (Gaur et al., 2021; Razmerita et al., 2015). Knowledge management practices, such as capturing and sharing employee expertise, have been linked to improved organizational performance and AI adoption (Saini & Marketing, 2013; Zhao et al., 2022)

The Resource-Based View (RBV) theory supports the idea that investing in human capital creates a competitive advantage, facilitating AI adoption (Gerhart & Feng, 2021; Wricht & Dunford Scott A Snell, 2001). HRM practices that focus on knowledge dissemination, organizational culture, and employee readiness can enhance AI adoption (Alqarni et al., 2023; Xiang et al., 2023). Similarly, the Knowledge-based View theory (KBV) perspective emphasizes knowledge as a strategic resource, with practical knowledge management supporting AI utilization (Alassaf et al., 2020; Zhao et al., 2022).

While AI adoption is positively linked to the availability of skilled human resources, the Palestinian context faces several challenges. These include limited financial and technological resources (Demaidi, 2023; Xiang et al., 2023), gaps in AI-related skills (Demaidi, 2023), cultural resistance to new technologies (Alkateeb & Abdalla, 2021), and regulatory hurdles (Reva et al, 2021) Addressing these challenges requires targeted efforts from the Palestinian government, European support, and public-private partnerships.

Finally, the sub-hypothesis is fully supported by empirical studies and the theoretical background of the different sectors and areas. HRM practices, such as human resource policies and management, staff training and incentivizing measures, investing in people and employee development, and organizational knowledge management, can facilitate the successful adoption of AI technologies. However, the findings showed that the Palestinian context may have unique challenges that must be addressed through targeted policies, strategies, and efforts from the Palestinian government, European financing, and training centers, as well as fostering public-private relationships.

H1d: *ICT people and human resources factor is positively related to AI.*

2.3.6 The Moderating Effect of Strategic Leadership

ICT readiness is a critical factor in the successful adoption of AI technologies across various sectors (Martínez-Plumed et al., 2021). In developed countries, where ICT infrastructure is generally more advanced, organizations tend to have a higher level of readiness for AI adoption (Brynjolfsson & Mcafee, 2017; Frangos, 2022). This readiness is often reflected in the availability of robust ICT hardware, well-established information systems, and a workforce with strong digital skills (Brynjolfsson & Mcafee, 2017; Frangos, 2022). However, even in developed nations, the adoption of AI technologies can be hindered by factors such as organizational culture, regulatory environments, and the need for specialized AI expertise (J. Yang et al., 2021).

In developing countries, including Palestine, the challenges associated with ICT readiness and AI adoption are often more pronounced. Limited access to advanced ICT infrastructure, outdated hardware, and a shortage of skilled personnel can significantly impact an organization's ability to implement AI solutions (Al-Ammary & Ghanem, 2024; Demaidi, 2023; ESCWA, 2022; Musleh, 2022; Tadj et al., 2023). These challenges are further compounded by economic constraints, political instability, and limited access to global technology markets, which can impede the development of a robust ICT ecosystem (ESCWA, 2022; Musleh, 2022; Tadj et al., 2023).

The role of strategic leadership in moderating the relationship between ICT readiness and AI adoption is particularly crucial in the Palestinian context. Influential leaders can drive organizational change, allocate resources strategically, and foster a culture of innovation that supports AI adoption (Almarzooqi, 2019; Bankins et al., 2024; Boal and Hooijberg, 2011; Kurup & Gupta, 2022). By prioritizing investments in ICT infrastructure, hardware upgrades, and employee training, strategic leaders can help overcome some of the barriers to AI adoption that are prevalent in developing countries (Fourie & Jacob Fourie, 2007; Kosgei et al., 2018; Tarisayi, 2024).

Empirical evidence supports the importance of leadership in technology adoption. Studies have shown that organizations with strong leadership support are more likely to successfully implement new technologies, including AI (Zhang & Huang, 2024). This is particularly relevant in the context of developing countries, where resource constraints and institutional challenges can make technology adoption more difficult (Chanyagorn & Kungwannarongkun, 2011; Demaidi, 2023; Madan & Yadav, 2016; Solomon Nsor-Anabiah et al., 2019). Strategic leaders can help navigate these challenges by aligning organizational goals with technological capabilities and fostering partnerships with external stakeholders (Fourie & Jacob Fourie, 2007; Kosgei et al., 2018; Tarisayi, 2024; Zhang & Huang, 2024).

The Technology-Organization-Environment (TOE) framework provides a sound theoretical lens through which to examine the relationship between ICT readiness, strategic leadership, and AI adoption (J. Yang et al., 2021). This framework suggests that technological factors (such as ICT infrastructure and hardware), organizational factors (including leadership and human resources), and environmental factors (such as regulatory environments and market conditions) all play important roles in technology adoption (J. Yang et al., 2021). In the Palestinian context, strategic leadership is a critical organizational factor that influences how effectively other elements of ICT readiness are leveraged for AI adoption (Anyango Oracha & Ogutu, 2021a).

Another relevant theoretical perspective is the Diffusion of Innovation theory, which emphasizes the importance of communication channels and social systems in the adoption of new technologies (Kurup & Gupta, 2022). Strategic leaders can act as change agents within their organizations, promoting the benefits of AI adoption and addressing concerns or resistance among employees. This is particularly important in contexts where there may be limited awareness or understanding of AI technologies (Fourie & Jacob Fourie, 2007; Kosgei et al., 2018; Tarisayi, 2024; Zhang & Huang, 2024).

In the Palestinian context, strategic leadership faces unique challenges in promoting AI adoption. These include limited access to international markets, restrictions on the movement of goods and people, and political instability (Al-Ammary & Ghanem, 2024). Despite these challenges, there are opportunities for strategic leaders to leverage existing strengths, such as a young and educated workforce, to drive AI adoption. By focusing on developing local talent, fostering innovation hubs, and collaborating with international partners, strategic leaders can help create an environment that is more conducive to AI adoption (Adobor et al., 2021; Fourie & Jacob Fourie, 2007; Kosgei et al., 2018; Quong & Walker, 2010b; Rowe, 2001; Tarisayi, 2024; Zhang & Huang, 2024).

The human resources factor is particularly critical in the context of AI adoption (Jatobá et al., 2023). Strategic leaders must not only invest in technical training but also foster a culture of continuous learning and adaptation (Luo et al., 2021). This is especially important in the rapidly evolving field of AI, where new technologies and applications are constantly emerging.

While the hypothesis suggests a positive moderating effect of strategic leadership on the relationship between ICT readiness and AI adoption, it is essential to note that this relationship is likely to be complex and context dependent. Factors such as organizational size, industry sector, and specific technological requirements can all influence the effectiveness of strategic leadership in promoting AI adoption (Moghaddamnia et al., 2023). Future research could explore these nuances in more detail, particularly in the Palestinian context, where empirical studies on AI adoption may be limited.

In conclusion, the hypothesis that strategic leadership positively moderates the relationship between higher levels of ICT readiness factors and AI adoption in the Palestinian context is supported by theoretical frameworks and empirical evidence from both developed and developing countries. However, the unique challenges faced in the Palestinian context, including limited ICT infrastructure, resource constraints, and political instability, highlight the critical role that strategic leaders must play in overcoming barriers to AI adoption. By focusing on developing ICT readiness across multiple dimensions and fostering a culture of innovation, strategic leaders can help position Palestinian organizations to leverage the potential benefits of AI technologies. Based on this, the primary strategic leadership moderating hypothesis (H2) posits that ICT readiness factors are positively related to AI adoption in the Palestinian context. This hypothesis is further broken down into four sub-hypotheses focusing on specific aspects of ICT readiness:

H2: *Strategic Leadership positively moderates the relationship between ICT readiness factors and AI adoption.*

2.3.7 ICT Infrastructure and AI Adoption: Strategic Leadership Moderation

The existing literature highlights the critical role of ICT infrastructure in facilitating AI adoption within organizations (Czarnul & Matuszek, 2019; Miseviciene et al., 2019; Mukhametov, 2022). A robust ICT infrastructure serves as the backbone for AI implementation, offering essential physical structures, network systems, data centers, and necessary security measures (Czarnul & Matuszek, 2019; Kurup & Gupta, 2022). Key elements, such as physical space, power supply, and cooling systems, are vital to support the hardware required for AI technologies (Parol et al., 2022). Furthermore, high-speed and reliable internet, along with strategically placed data centers, ensures the efficient processing of data (Mukhametov, 2022). Secure network infrastructure, including firewalls, access controls, and encryption protocols, is also crucial for protecting AI systems and the sensitive data they handle(Kurup & Gupta, 2022).

Empirical studies demonstrate a positive relationship between ICT infrastructure and AI adoption across various industries and regions (Czarnul & Matuszek, 2019; Mukhametov, 2022). However, this relationship is complex and influenced by various organizational factors, particularly the role of strategic leadership. Strategic leadership plays a crucial role in shaping an organization's strategic direction, fostering a conducive culture, and aligning resources to achieve its goals (Adobor et al., 2021; Chatterjee et al., 2022; Fourie & Jacob Fourie, 2007; Mjaku & c, 2020; Rowe, 2001). In the context of AI adoption, strategic leaders are responsible for setting the organization's vision and defining strategic goals, which often include embracing AI technologies to maintain competitiveness (Adobor et al., 2021; Chatterjee et al., 2022; Fourie & Jacob Fourie, 2007; Mjaku & c, 2020; Rowe, 2001). They also ensure that AI initiatives are adequately funded, balancing both financial and non-financial considerations, while keeping ethical and societal implications in mind (Muhsin Thaji et al., 2022).

A strong organizational culture is essential for successful AI adoption, and strategic leaders foster this by promoting innovation, risk-taking, and continuous learning (Khalid Thaher Amayreha*, 2020). Leaders must also emphasize ethical practices, ensuring transparency and accountability in AI deployment to mitigate risks (Almarzooqi, 2019; Boal and Hooijberg, 2001; Mjaku & c, 2020; O'Shannassy, 2021). Moreover, strategic leaders leverage an organization's core competencies, such as expertise in data analytics or technical capacity, to drive the success of AI adoption (Adobor et al., 2021; Almarzooqi, 2019; Huq et al., 2019). They also focus on developing human resources by investing in skills related to data science and AI engineering, ensuring the workforce is equipped for AI integration (Rowe, 2001). Additionally, building strong relationships with external stakeholders, such as academic institutions and industry partners, helps facilitate knowledge sharing and access to advanced AI technologies (Adobor et al., 2021; Almarzooqi, 2019; Huq et al., 2019).

A case study by IFEANYICHUKWU (2024) highlighted the role of strategic leaders in securing AI-powered solutions in healthcare through substantial investments in scalable server systems and secure networks. Strategic leaders are well-positioned to direct the allocation of resources within the organization, often focusing on ICT infrastructure investments that support AI technologies, such as cloud-based AI systems (Oguejiofor et al., 2023). For example, leadership was critical in the successful implementation of Six-Sigma technology in Saudi Arabia, emphasizing the need for organizational buy-in, training, and building IT infrastructure (Huq et al., 2019). Strategic leaders can also form partnerships with AI technology providers or collaborate with other organizations that have successfully implemented AI, helping to overcome limitations in existing ICT infrastructure (Oguejiofor et al., 2023).

Several theoretical frameworks support this hypothesis. The Resource-Based View (RBV) suggests that strategic leaders can exploit an organization's resources, including ICT infrastructure, to create a sustainable competitive advantage (Rowe, 2001). Similarly, the Upper Echelons Theory argues that the characteristics and decisions of top management teams, including strategic leaders, directly influence organizational outcomes, such as AI adoption (Anyango Oracha & Ogutu, 2021a).

Despite the general validity of the hypothesis, applying it to the Palestinian context presents unique challenges. Palestine faces political instability, economic constraints, and limited access to resources, which hinder the development of robust ICT infrastructure and high-tech solutions like AI (Demaidi, 2023). Political instability has distorted urban development in regions like Jerusalem-Ramallah, affecting long-term planning and technological implementation (Raddad & Samat, 2016). Furthermore, the longstanding conflict between Israel and Palestine poses significant political and economic challenges, further complicating efforts to implement advanced technologies (Tadj et al., 2023). Palestine also lacks a well-established culture of strategic leadership, which affects ICT infrastructure development (ESCWA, 2022). Additionally, limited access to skilled human capital and exclusion from international collaborations reduce the country's potential for leveraging AI technologies (Dalal et al., 2023).

Despite these challenges, Palestinian organizations can address these issues through partnerships with external stakeholders and increased participation in international collaborations. By fostering frequent interactions and strategic partnerships, Palestinian organizations can overcome some of the limitations they face in ICT infrastructure and leadership.

In conclusion, the sub-hypothesis H2a, which posits that strategic leadership positively moderates the relationship between ICT infrastructure and AI adoption, is well-supported by literature, empirical evidence, and relevant theories. However, the unique challenges facing Palestine must be addressed through specialized interventions and collaborative efforts to fully realize the potential of AI adoption for socio-economic development.

$H2_a$: *Strategic Leadership positively moderates the relationship between the ICT infrastructure factor and AI adoption.*

2.3.8 ICT Hardware and AI Adoption: Strategic Leadership Moderation

Personal devices such as personal computers, printers, and scanners, which are key components of ICT readiness drive individual productivity and organizational efficiency. Similarly, quality and availability significantly affect AI technologies (Akinola, 2023;

Nandhini et al., 2022a, 2022b; Ranjit Singh & Muniandi, 2012). A case in point is a Nigerian academic library where AI tools like natural language recognition and machine learning have achieved prominence because of the availability of sufficient personal devices (Akinola, 2023). Similarly, in Malaysian schools, the willingness of teachers to integrate ICT tools is influenced by the availability and maintenance of personal devices (Ranjit Singh & Muniandi, 2012). Private servers are essential for internal data storage and processing. They provide the infrastructure needed for secure and efficient data management, which is crucial for AI applications. The study on the adoption of ICT systems in Indian manufacturing MSMEs highlights the importance of robust ICT infrastructure, including private servers, for technological advancement (Nandhini et al., 2022a). In the context of smart cities in China, the adoption of AI and IoT technologies is hindered by challenges related to ICT infrastructure, including private servers (Wang et al., 2021). Furthermore, public servers are crucial for some AI applications since they require real-time processing in large datasets. An example can be drawn from Sub-Saharan Africa, where mHealth solutions are integrated, and public servers are used in the sharing of health data between the provinces (Solomon Nsor-Anabiah et al., 2019). Again, developing countries lack sufficient public server infrastructures, making it hard to adopt AI solutions (Adebayo Olusegun Aderibigbe et al., 2023). In our study, we focus on the role strategic leadership involves in directing the organization or business to a clear vision. Several firms may not achieve the ability to invest in ICT hardware unless led strategically (Bankins et al., 2024; Boal and Hooijberg, 2011; Kosgei et al., 2018; Mjaku & c, 2020; Mo, 2012a; Rowe, 2001). For instance, the Office of the Director of Public Prosecutions in Kenya focused its investment on ICT hardware to gain control of the crime rate based on the strategy and the strategic direction of the organization (Kosgei et al., 2018). Balanced controls, which include financial and non-financial metrics, were critical in the evaluation of the AI transition process. Leadership is instrumental in developing these controls to evaluate the performance of ICT hardware (Kosgei et al., 2018). The study of strategic leadership and performance within the Kenyan INGOs setting reviews the significance of balanced controls in achieving organizational performance (Anyango Oracha & Ogutu, 2021b). Core competencies, such as technical expertise and data management capabilities, are critical for AI adoption. Strategic leaders must focus on developing and leveraging these competencies (Anyango Oracha & Ogutu, 2021b). The study on strategic management and leadership highlights the role of leadership in transforming organizations through the right strategies (Mjaku & c, 2020). Investing in human capital, including training and development, is essential for successful AI adoption. Leaders must ensure that employees have the necessary skills to utilize ICT hardware effectively (Mjaku & c, 2020). The research on AI in developing countries emphasizes the importance of capacity building(Adebayo Olusegun Aderibigbe et al., 2023). Moreover, several theories confirm this postulated hypothesis. Resource-Based View theory, for example, a theory that a business organization can gain a competitive advantage through its unique resources and capabilities (Gerhart & Feng, 2021; Kosgei et al., 2018). Therefore, from the perspective of AI this would mean that the ICT hardware parts are resources that can be capitalized on to outbeats competitors (Blurton, 1999a; Chatterjee, Chaudhuri, et al., 2021). A strategic leadership role is to identify these resources and maximize them to gain from them. Open Systems Theory is another theory that asserts how an organization interacts with the external environment (Kosgei et al., 2018). In the case of AI, available data or ICT to be purchased and used from public servers also forms part of interaction with the external environment (Zeng et al., 2021). Therefore, a strategic leader should oversee that the organization is ready and open to integrate external resources to its entities. Institution Theory focuses on the impact of institutional norms on organizational behaviors(Kosgei et al., 2018). It implies that ICT hardware components are essential resources for enhancing strategic leadership to create a competitive advantage (Abu Mansour, 2022; Bankins et al., 2024;

Chanyagorn & Kungwannarongkun, 2011; Rowe, 2001). For AI adoption, this interaction involves integrating external data and technologies through public servers (Kosgei et al., 2018).. Also, strategic leaders should secure adequate organization openness to frequent external collaborations and innovations in this process (Kosgei et al., 2018).

In Palestine, such leaders should mostly comply with various regulators and adapt AI to the organization's requirements. Evidence from some empirical tests in different industries also supported the strategic leadership hypothesis. Therefore, it could be considered central to overcoming the challenges that stage AI's fast implementation, particularly in the Palestine context.

H2b: *Strategic Leadership positively moderates the relationship between the ICT Hardware factor and AI adoption.*

2.3.9 ICT Information System / Software and AI Adoption: Strategic Leadership Moderation

Research indicates that the integration of ICT into business processes leads to more efficient operations and enhanced decision-making. In the educational sector, the incorporation of software in early childhood education has been shown to improve learning outcomes by increasing student engagement (Iancu, 2023). Similarly, in the strategic decision-making domain, studies demonstrate that implementing ICT systems provides organizations with more opportunities, reduces threats, and improves overall performance (Almarzooqi, 2019; Indrasari & Pamuji, 2024; Mahdi & Almsafir, 2014b; J. Yang et al., 2024). For example, in larger financial services companies, strategic leadership has enabled the development of AI-powered platforms for fraud detection and risk assessment (J. Yang et al., 2024).

The Information Systems Success Model, as described by DeLone and McLean, further underscores the importance of quality dimensions—system quality, information quality, and service quality—in ensuring the success of ICT systems (Makokha & Ochieng, 2014). Strategic leadership plays a crucial role in securing these dimensions by providing the necessary resources, oversight, and support (Almarzooqi, 2019; Boal and Hooijberg, 2001; Mjaku & c, 2020; Moghaddamnia et al., 2023; J. Yang et al., 2021). Moreover, strategic leadership fosters a culture of innovation and change, which is essential for AI adoption (Almarzooqi, 2019.; Boal and Hooijberg, 2001; Mjaku & c, 2020; Moghaddamnia et al., 2023; J. Yang et al., 2021). A study on AI chatbots in e-retailing revealed that these quality dimensions positively influence customer experience and satisfaction (J. Chen et al., 2021).

In conclusion, the hypothesis that strategic leadership positively moderates the relationship between ICT information and software factors and AI adoption in the Palestinian context is supported by both empirical evidence and theoretical perspectives.

H2$_c$: *Strategic Leadership positively moderates the relationship between the ICT information system and software factor and AI adoption.*

2.3.10 ICT People /Human Resources and AI Adoption: Strategic Leadership Moderation

Effective human management policies are vital for creating an environment conducive to technology adoption, including AI. For instance, in Malaysia's hospitality industry, human resource strategies have improved competitiveness by enhancing service quality and employee performance (Twan, 2023). Additionally, continuous learning and development equip employees to adapt to new technologies (Ayodeji, 2015). Investment in employee development, including training and seminars, is crucial for fostering innovation. For example, blockchain technology has improved learning records and real-time HRM data updates, highlighting the importance of developing employees to support technology adoption (Vijh et al., 2023).

Organizational knowledge management is another key factor, ensuring that members can process and apply their knowledge to implement new technologies. The Virtual Math

Teams (VMT) environment illustrates how knowledge sharing promotes group cognition and problem-solving, enhancing technology adoption (Stahl, 2007).

Strategic leadership significantly influences the relationship between human resources and AI adoption (Muhsin Thaji et al., 2022; Tarisayi, 2024). According to the Upper Echelons Theory, top executives' characteristics and actions shape organizational outcomes. Leaders with a forward-thinking approach align resources and capabilities with strategic goals to drive technology adoption (Anyango Oracha & Ogutu, 2021a). The Resource-Based View (RBV) theory also emphasizes the role of strategic leadership in leveraging resources for competitive advantage, which supports AI adoption and improves organizational performance (Chatterjee et al., 2022).

Additionally, Leaders must be able to navigate complex ethical dilemmas that arise from AI adoption, balancing organizational goals with ethical considerations (Almarzooqi, 2019; Huq et al., 2019)

In the Palestinian context, strategic leadership helps facilitate the transition to AI technologies by training staff, adjusting business processes, and managing cultural changes (Sun & Medaglia, 2019; Wairiuko et al., 2018). Empirical evidence and theoretical frameworks support the hypothesis that strategic leadership positively moderates the relationship between human resources and AI adoption in Palestine, aligning resources with technology goals and enhancing ethical practices and social capital. Therefore, developing strategic leadership is critical to the successful adoption of AI in Palestinian organizations.

H2$_d$: *Strategic Leadership positively moderates the relationship between the people and human resources factor and AI adoption.*

2.3.11 The Moderating Effect of Perceived Attributes of Innovation

Kang and Westskytte (2018) and Ayong and Naidoo (2019) , concluded that perceived innovation attributes in the financial industry and South African organizations have a direct impact on the likelihood of adopting any new technology. Specifically, it was reported that relative advantages and compatibility were the most critical factors in the decision to adopt AI.

Kang and Westskytte (2018) used the DOI and Technology-Organization-Environment (TOE) frameworks to demonstrate how AI-based cybersecurity solutions can be implemented in the banking industry. They found that the interaction between complexity and relative advantage could be more straightforward: While complexity reduces the likelihood of adoption, advantageous outcomes are positively impacted by relative advantage. A lack of knowledge and expertise in AI and cybersecurity has been diagnosed as a significant impediment in this case. Ayong and Naidoo (2019) conducted qualitative research on the adoption of AI by organizations in South Africa. They combined DOI theory, institutional theory, and TOE framework in their research—technology integration, compatibility, and information technology support emerge as essential drivers of AI adoption.

Chen (2019) researched the adoption of AI in the Chinese telecom industry through TOE and DOI's lens. They share specific characteristics, including compatibility, complexity, and relative advantage, as well as government involvement and vendor support, that have the most significant impact on AI adoption in the Chinese telecom industry. Similarly, (Truvé et al., 2019) explored Swedish manufacturing SMEs' AI adoption by basing their research on the transformation and overlap of the theories of DOI and TOE. The lack of Norms and Market Pressure, as well as high technical aptitude and know-how and inadequate funds to buy costly contraptions, has hindered the deployment of AI in Swedish SMEs.

In conclusion, the diffusion of innovation theory allows for a meaningful understanding of the determinants of the adoption of new technologies, such as AI. The perceived attributes of innovation, in turn, and especially relative advantage and compatibility, play a crucial part in the process of AI adoption. For this reason, it is assumed that the perceived attributes have a positive moderate impact on ICT readiness and the adoption of AI. In other words, these findings will help hypothesize the importance of the attributes for the promotion of new technologies. Following this, the primary moderating hypothesis (H3) is that perceived attributes of innovation (Relative advantage and Compatibility) moderate the relationship Between ICT readiness factors and Artificial intelligence in Palestine. This hypothesis is further broken down into eight sub-hypotheses. The other eight sub-hypotheses include the salient points on which ICT readiness factors were based.

H3: *Perceived attributes of innovation (Relative advantage/Compatibility) moderate the relationship Between ICT readiness factors and AI adoption.*

2.3.12 ICT Infrastructure and AI Adoption: Relative Advantage Perceived Attributes Moderation

The relative advantage is the perceived degree to which an innovation is better than the idea it supersedes (Rogers et al., 2003). In the case of AI, such advantages may include higher levels of efficiency, reduced costs, higher capacities, and a better competitive position than all methods this technology can replace (Bhagat & Shah, 2023; Umar et al., 2024). The relative advantage of AI has a significant impact on technology adoption (Musa Ibrahim & Gbaje, 2015). Organizations will only use or implement AI and machine learning if they see clear advantages over existing technologies. Such advantages involve improving analytical functionality, using AI/ML models to automate routine tasks, or even having access to big data analysis capabilities (Bhagat & Shah, 2023; Umar et al., 2024).

Based on that, the Physical structures in ICT for AI include data centers, which contain computer systems and associated elements (Abu Mansour, 2022; Chanyagorn & Kungwannarongkun, 2011). Telecommunications and storage systems have to be built to support significant amounts of data and complex processing accomplished with these Ais (Bisola Beatrice Oguejiofor et al., 2023; Roh et al., 2019a, 2019b).Given the intensive nature of AI computations, those should be able to handle high power and cooling requirements (Bhagat & Shah, 2023).

Moreover, Network security is also a critical key element of ICT infrastructure for AI (Ahmed et al., 2009; Alotaibi, 2023; M. Chen et al., 2013). Therefore, AI systems frequently handle sensitive data and have become a prime target for cyber threats (Ahmed et al., 2009; Alotaibi, 2023; M. Chen et al., 2013). Protecting the integrity of data and barring unauthorized access to sensitive information relies on a robust network security posture. This includes the use of advanced cryptographic techniques, intrusion detection systems, and continuous monitoring mechanisms (Choi et al., 2021; Gulia et al., 2022).

The finance sector offers the most explicit evidence concerning how relative advantage can moderate the relationship between AI adoption and ICT infrastructure. Among them, in the study in South Africa on blockchain adoption factors of supportability and scalability, they are intrinsic parts of ICT infrastructure that will likely improve the readiness for adopting this type of AI technology (blockchain). The growing realization of the capabilities that blockchain offers is resulting in financial institutions pushing into areas such as digital identity and transactions, making their ICT strategies more important than ever (Adams et al., 2023). In education, the adoption of AI-driven solutions such as learning analytics and e-learning platforms depends significantly on ICT infrastructure. The study on Infrastructure as a Service-based e-learning in Nigerian higher education institutions shows that relative advantage (including cost savings and improved learning processes) encourages the adoption of these technologies (Tom et al., 2019). At this point, Tom et al. (2019) concluded that the robust ICT infrastructure implies the effective utilization of AI, which supports the hypothesis that there is a significant impact of a higher level of relative advantages on enhancing the relationship between ICT infrastructure and the ability to adopt artificial intelligence (Tom et al., 2019) .In the manufacturing sector, AI adoption for supply chain finance and operations optimization also illustrates this hypothesis. The study on supply chain finance adoption in Chinese manufacturing firms indicates that information sharing, and digitization (aspects of ICT infrastructure) are crucial for adopting AI-enabled processes (Nguema et al., 2021). As the perceived benefits of AI in enhancing supply chain effectiveness become more apparent, the dependency on substantial ICT infrastructure increases (Nguema et al., 2021). The retail sector, with its increasing use of AI for customer data analytics and inventory management, also supports the hypothesis. Robust ICT infrastructure allows retailers to leverage AI technologies more effectively and significantly, as they recognize the advantages of AI in providing personalized shopping experiences and operational efficiencies (J. Chen et al., 2021).

Empirical evidence across various sectors shows that the relative advantage of AI moderates the relationship between ICT infrastructure and adoption of AI. As the perceived benefits of AI technologies grow, the need for a robust ICT infrastructure becomes increasingly significant. This connection is particularly evident in industries like healthcare, finance, education, manufacturing, and retail, where AI adoption is essential for achieving strategic and operational improvements. The reviewed studies align with this hypothesis, confirming a clear trend: the more significant the perceived advantage of AI, the stronger the impact of ICT infrastructure on its adoption.

H3$_a$: *Relative advantage moderates the relationship between the ICT infrastructure factor and AI adoption, such that as the Relative Advantage becomes high, the relationship becomes stronger.*

2.3.13 ICT Hardware and AI Adoption: Relative Advantage Perceived Attribute Moderation

Studies on the adoption of mobile technologies in healthcare have highlighted the role of perceived advantages, such as improved patient care and operational efficiency, in driving adoption (Kalpande & Toke, 2022). There will be a great need for private servers or internal use in the storage of data to handle large amounts of production data generated through artificial intelligence applications. According to Bonsu et al. (2023), the capacity and reliability of private servers are critical considerations when determining whether a cloud-based ERP system will be adopted or avoided. It was because they realized a high relative advantage of cloud ERP implementation concerning its expandable and less expensive nature as long as private server infrastructure remained stable. In other words, the private server quality has a more significant impact on AI adoption when the perceived benefit of AI technologies is significant.

On the other hand, public servers are an essential part of AI applications that enable the organization to use external servers for better communication through interaction with its external stakeholders (T. Chen et al., 2023; Demaidi, 2023; Sun & Medaglia, 2019). In Colombia, the investment in public server infrastructure has been found to have a significant impact on citizens' adoption of online tax filing and payment services. As a result, the study highlighted the relative advantage of e-government services in terms of convenience and efficiency, which was made possible by a reliable public server infrastructure (Ramirez-Madrid et al., 2022). In this example, the existence and good quality of public servers lead to AI adoption due to a relative advantage that is perceived by both the organization itself and its stakeholders.

Organizations are more likely to invest in AI hardware when they see clear benefits in terms of efficiency, productivity, and cost savings. This is consistent with Rogers' theory of relative advantage, which holds that innovations with perceived benefits are more likely to be adopted (Miller, 2015a).

In conclusion, Relative advantage moderates the relationship between ICT hardware factor and AI adoption in the Palestinian context, as evidenced by both empirical evidence and theoretical perspectives.

H3b: *Relative advantage moderates the relationship between ICT hardware factor and AI adoption, such that as the Relative Advantage becomes high, the relationship becomes stronger.*

2.3.14 ICT information/system and AI Adoption: Relative Advantage Perceived Attribute Moderation

To better understand the relative advantages of Artificial Intelligence (AI) systems and their moderating role in the relationship between Information and Communication Technology (ICT) and AI adoption, it is essential to delve into empirical evidence across various sectors, including healthcare, education, and e-commerce, and discuss the relative advantages of AI systems alongside suitable ICT software and information systems. The adoption of AI in the healthcare industry has drastically improved diagnostic precision, patient care, and operational effectiveness (T. Chen et al., 2023). Indeed, AI-based chatbots in public healthcare administrations allow for better service delivery and patient involvement. The relative advantage of AI will be its capacity to quickly and accurately examine vast amounts of data and produce actionable information that can have a positive impact on patient results (T. Chen et al., 2023). Another study in the Nigerian healthcare sector highlighted the adoption of cloud-based Enterprise Resource Planning (ERP) systems that support AI and, therefore, can be used to quantify improved resource management and decision-making (Usman et al., 2019).

The education sector has seen the adoption of AI to enhance the student learning experience, particularly in higher education in India, where AI chatbots have been employed to improve productivity, communication, and teaching assistance (Sandu & Gide, 2019). The relative advantage here includes personalized learning experiences and efficient administrative processes (Sandu & Gide, 2019). The role of organizational sub-cultures in higher education's adoption of Open-Source Software (OSS) for teaching and learning further underscores the significance of ICT information/software factors in facilitating AI adoption (Williams Van Rooij & Denver, 2010)

In the e-commerce sector, the adoption of Facebook for marketing by small and medium enterprises (SMEs) in northwestern Nigeria illustrates the impact of ICT software on enhancing business performance through AI-driven analytics and customer engagement (Abdullahi et al., 2022).

Overall, relative advantage plays a crucial role in moderating the relationship between ICT information/software factors and AI adoption, as supported by empirical evidence from healthcare, education, and e-commerce research. Such relative benefits, including high efficiency, accuracy, and personalization in services, make ICT factors more important in affecting the decision to adopt. Exploiting the potential of AI in Palestine requires identifying these comparative advantages and ensuring that proper ICT software and information systems are invested to optimize availability across all sectors.

H3$_c$: *Relative advantage moderates the relationship between ICT information/systems factor and AI adoption, such that as the Relative Advantage becomes high, the relationship becomes stronger.*

2.3.15 ICT People/Human Resources and AI Adoption: Relative Advantage Perceived Attribute Moderation

The adoption of artificial intelligence by many organizations in different sectors has become a key area of interest in the fields of information and communication technology and human resources (Sadashiv Jadhav, 2021b; Tornatzky & Klein, 1982). This literature review seeks to unpack the hypothesis that the moderating effect of Relative Advantage enhances the relationship between ICT personnel/human resource factors and the adoption of AI in the Palestine context. To ascertain this hypothesis, we will look at empirical evidence from various sectors, evaluate the relative advantages of AI between AI and the status quo, and weigh the merits and demerits of human resource policy and practices that facilitate the adoption of AI. The discussion will be based on relevant theories, including Diffusion Theory and Resource-Based View.

The firm's Resource-Based View (RBV) posits that organizations can achieve a sustainable competitive advantage through the acquisition and management of valuable, rare, inimitable, and non-substitutable (VRIN) resources and capabilities.(Gerhart & Feng, 2021; Touil & Jabraoui, 2019). In the context of AI adoption, human resources (knowledgeable ICT personnel and supportive HR policies) can be considered strategic assets that facilitate the integration and effective use of AI technologies (Dunford et al., 2001; Gerhart & Feng, 2021).

Studies have shown that the adoption of AI and HR analytics transforms HRM from its traditional administrative functions to more strategic roles, enhancing organizational performance and competitiveness (Arora et al., 2021; Rehman, 2023). AI systems offer relative advantages such as improved decision-making, efficiency, and productivity in HR functions like talent acquisition, training and development, and performance appraisal (Arora et al., 2021). For instance, the integration of electronic HRM (E-HRM) systems in the tourism and hospitality industry has been linked to sustainable competitive advantages through sustainable innovation and organizational agility (Alqarni et al., 2023).

Ayong & Naidoo (2019) conducted a qualitative study on the adoption of AI in South African enterprises and found that adoption choices regarding human resources are influenced by relative advantage.When training and development connected to AI is clearly beneficial to employee productivity, job happiness, or organizational competitiveness, organizations are more willing to invest in it.

The successful adoption of AI in human resource management (HRM) depends on implementing supportive policies and practices that align with the capabilities of AI technology. A critical component is the development of human management policies and investment in people. Organizations need to provide training and development programs to ensure HR personnel acquire the necessary skills to effectively utilize AI technologies (Arora et al., 2021). Additionally, AI adoption requires fostering a culture of continuous learning and innovation, which involves not only formal education but also an environment that encourages experimentation and the adoption of new technologies to enhance various aspects of organizational operations (Huang et al., 2024). Furthermore, AI systems play a vital role in enhancing organizational knowledge management by facilitating the capture, storage, and dissemination of knowledge, which supports better decision-making and drives innovation (Rehman, 2023).

While specific studies focusing on the Palestinian context were not identified in the provided sources, the general principles and findings can be extrapolated to suggest that the relative advantages of AI systems could similarly influence ICT personnel and HR factors in Palestine. The successful adoption of AI in Palestine depends on the extent to which organizations can leverage these relative advantages through supportive HR policies and practices.

In conclusion, the moderating effect of Relative Advantage on the link between ICT personnel, human resource factors, and AI adoption is supported by both theoretical frameworks and empirical evidence. The relative advantages offered by AI systems, such as improved efficiency, decision-making, and competitive advantage, underscore the importance of supportive HR policies and practices. These include investments in staff education, encouragement of a learning culture, and practical knowledge management.

H3$_d$: *Relative advantage moderates the relationship between ICT people, human resources factors, and AI adoption, such that as the relative advantage becomes high, the relationship becomes stronger.*

2.3.16 ICT Infrastructure and AI Adoption: Compatibility Perceived Attribute Moderation

According to DOI, compatibility is one of the critical attributes that determines the rate of innovation adoption. Innovations that are more compatible with the intended users' existing values, past experiences, and needs are more likely to be adopted (Miller, 2015a). In the healthcare sector, the adoption of AI technologies can significantly enhance service delivery, patient care, and operational efficiency. A study on the adoption of antenatal care conversation mapping among healthcare providers in Saudi Arabia applied the diffusion innovation theory, highlighting the importance of compatibility alongside other DOI variables (Alhashem et al., 2023). Although this study is not directly situated in the Palestinian context, it underscores the relevance of compatibility in the successful adoption of innovative healthcare solutions.

The education sector's adoption of ICT and AI technologies can revolutionize teaching and learning processes. A study examining the determinants of ICT adoption among academic staff in Bauchi State emphasized the role of technological factors, including infrastructure, perceived usefulness, and ease of use, as critical drivers (Ahmad & Ibrahim, 2017). While the study does not explicitly address compatibility, the emphasis on technological factors aligns with the hypothesis that compatibility with existing ICT infrastructure is crucial for the adoption of AI.

The research done by Nusir et al. (2023) on intelligent city adoption in Jordan argued that people's interest in using innovative city services was directionally proportional to the degree of ICT infrastructure resource availability. In other words, if new technology can run concurrently with the existing infrastructure, it is likely compatible with the older systems and, hence, can be adopted quickly. Businesses are likely to buy infrastructure AI if they cooperate nicely with their existing system and operations.

Besides that, the Technology-Organization-Environment (TOE) framework can provide additional theoretical justification for the described hypotheses. Researchers who created this theoretical approach argued that technological, organizational, and environmental contexts shape innovation adoption. If it appears that compatibility within the technological context influences the relationship between ICT infrastructure and AI adoption, this finding can be explained by the fact that compatibility modulates the match between the innovations and the existing information technology infrastructure (Miseviciene et al., 2019; Mohamad et al., 2018).

In conclusion, the current study concluded that the compatibility hypothesis on moderating the relationship between ICT infrastructure variables and AI adoption works in different sectors, and thus, it was supported theoretically. These three examples from healthcare, education, and finance show how compatibility is essential to generate the required momentum for AI technologies. More so, theoretical frameworks like DOI theory and TOE framework highlight the compatibility notion in their determinants of innovation adoption as one measure. Therefore, a higher level of compatibility between AI technologies and existing ICT infrastructure is well poised to strengthen the correlation between these types of infrastructure variables and successful AI adoption in Palestine.

H3$_e$: *Compatibility moderates the relationship between the ICT infrastructure factor and AI adoption, such that as Compatibility becomes high, the relationship becomes stronger.*

2.3.17 ICT Hardware and AI Adoption: Relative Advantage Perceived Attribute Moderation

AI technologies have been integrated into personal tools and gadgets such as smartphones and smart glasses (Kumar et al., 2023; Zeng et al., 2021). The compatibility of these AI applications accommodated within these personal devices depends on their specifications (Kumar et al., 2023; Zeng et al., 2021). For instance, it must meet the processing, storage, and power needs of the device, as well as energy consumption. Moreover, more excellent compatibility implies that the AI technology can be successfully adopted and used within the personal device (Kumar et al., 2023; Zeng et al., 2021).

Additionally, a study by (Bu et al., 2023) proves the importance of compatibility for AI technologies designed to be computationally robust. More specifically, they need to be compatible with powerful server hardware to succeed, as is the case with big data analytics, parametric design, and complex simulations. Determining the public and private server compatibility relevant for the AI adoption of the latter kind will depend on these capacities and capabilities. In this case, AI technology may be adopted and used effectively in settings within which the public and private servers can support these applications without compromising performance (Bu et al., 2023).

Regarding the influential determinant of the adoption of AI applications in online learning environments in governmental institutions, it was determined that the compatibility with existing technological hardware devices of these institutions was an influential positive determinant in this context as well (Almaiah, Alfaisal, et al., 2022b). On the other hand, there are AI technologies found in medical devices within the EU where the degree to which the AI is compatible with the EU's regulatory and ethical structures can affect the adoption of these AI technologies in a specific context (Braun & Harasimiuk, 2023).

Compatibility plays a critical role in the adoption of AI technologies(Usman et al., 2019). It ensures that new technologies can be integrated seamlessly with existing ICT hardware, which is essential for their functionality and effectiveness. In the Palestinian context, where technological infrastructure may vary significantly, the compatibility of AI technologies with personal devices, private servers, and public servers becomes a determining factor in their adoption (Musleh, 2022; Raddad & Samat, 2016; Tadj et al., 2023).

In summary, all the above analyses indicate that the hypothesis stating that any higher compatibility of ICT hardware with AI technology would lead to a more substantial level of adoption relationships in Palestine is empirically supported among several sectors.

H3f: *Compatibility of the relationship between ICT hardware factor and AI adoption, such that as the Compatibility becomes high, the relationship becomes stronger.*

2.3.18 ICT information/system and AI Adoption: Relative Advantage Perceived Attribute Moderation

Sambit & Hazra (2017) found in their research on ICT adoption software systems in university libraries in West Bengal that compatibility was a major factor contributing to the likelihood of a new technology being perceived as better and later adopted. This suggests that when new technologies are compatible with existing systems and practices, they are more likely to be adopted (Sambit & Hazra, 2017).

The results of the study on small businesses adopting cloud computing showed that compatibility was among the significant determinants of adoption in terms of intent to use cloud computing, and the same can be said about AI adoption. Both cloud computing and AI require that new technological solutions be integrated into pre-existing ICT systems (Powelson, 2011).

The primary challenge in enhancing compatibility in the Palestinian context lies in the variability of existing ICT infrastructures and the limited resources available for comprehensive system upgrades (Musleh, 2022; Raddad & Samat, 2016; Tadj et al., 2023). However, this also presents an opportunity to design AI solutions that are inherently flexible and adaptable to diverse systems, thereby increasing their compatibility and potential for adoption.

Ultimately, for AI adoption to be successful in Palestine or similar regions, stakeholders must focus on developing and implementing AI technologies that are not only technologically advanced but also highly compatible with existing ICT software and information factors. This approach will likely increase the effectiveness and acceptance of AI, thereby maximizing its benefits in various sectors.

H3$_g$: *Compatibility moderates the relationship between ICT information/systems factor and AI adoption, such that Compatibility becomes high, and the relationship becomes stronger.*

2.3.19 ICT people/Human Resources and AI Adoption: Relative Advantage Perceived Attribute Moderation

According to the Resource-Based View, competitive advantage is gained through the accumulation of internal capabilities and resources (Gerhart & Feng, 2021). In this context, for AI adoption, one of the most important factors is the alignment (compatibility) of AI technologies with existing human resources–related capabilities of an organization, such as staff education, knowledge management, and human management policies (Ariana et al., 2020; Gerhart & Feng, 2021; Marius Martin et al., 2011). In other words, staff education, knowledge management, and human management policies of an organization should be aligned with the use of AI, which can enhance an organization's ability to reap strategic advantages through AI use (Ariana et al., 2020).

Moreover, the degree of compatibility of new AI with existing ICT people and human resources management practices appears to be vital for successful technology transfer (Ariana et al., 2020; Gerhart & Feng, 2021; Marius Martin et al., 2011). For instance, the adoption of e-government technologies was significantly influenced by the readiness and capacity of the ICT human resources, which include the technical and management capabilities for ICT (Ariana et al., 2020).

Similarly, in the case of the healthcare sector, the adoption of mobile health applications was facilitated by the compatibility of these innovations with the existing hospital systems and the capacity of the ICT human resources to handle the innovations (Ngongo et al., 2019).

Moreover, effective human resources management (HRM) policies focus on managing investments in staff education, training, and development. Sensible investments ensure that the staff is equipped with the relevant skills and knowledge to work with AI technologies (Böhmer & Schinnenburg, 2023a; Budhwar et al., 2022; Jatobá et al., 2023). This leads to greater compatibility between human resources practices and new technologies (Jatobá et al., 2023).

Investment in people, especially when it comes to training and development on AI and relevant technologies, enhances the overall readiness for technology (Al-Alawi et al., 2023; Böhmer & Schinnenburg, 2023a; Budhwar et al., 2022; Jatobá et al., 2023). It has also been learned that organizational knowledge management practices facilitate excellent compatibility. This means that the sharing and integration of knowledge about AI ensures that all employees understand the technology and are ready for it (Al-Alawi et al., 2023).

The compatibility of existing ICT human resources elements with AI technologies enhances moderation. The higher the compatibility between an organization's AI technologies and its current practices, systems, and culture, the easier it is to integrate new technology successfully. Integration of these AI tools ensures that they do not oppress the current tasks but rather act as complementary tasks. Thus, this makes the technology adopted more efficient and effective due to people's good acceptance of new methodologies.

This becomes even more important in a Palestinian context. Before adopting AI technologies, organizations must perform a rigorous assessment of their current ICT capabilities and human resources practices. This will assist in spotting loopholes and points essential to change and ensure they are more compatible for better use of AI integrations.

To conclude, this study provides theoretical frameworks supported by the empirical evidence that compatibility moderates ICT people and HR factors on AI adoption in the Palestinian context. For organizations to embrace AI technologies, they must strive to increase their compatibility, and this can be achieved through adequate human capital management parameters, investment in the knowledge of employees, and exchange of know-how within the organization. These efforts will do much more than make it easier for AI to integrate and be used – they will also make it possible to unlock the true potential of these technologies, supporting their organizations on a path to success.

$H3_h$: *Compatibility moderates the relationship between ICT people and human resources factors and AI adoption, such that as Compatibility becomes high, the relationship becomes stronger.*

2.4 Chapter Two Summary

This chapter explores the context of AI adoption in Palestine through an in-depth review of existing literature. IT presents the conceptual framework developed to study how ICT readiness factors influence AI adoption in this challenging environment. It proposes that core ICT infrastructure components like networks, hardware, information systems, and human resources positively impact AI adoption potential. However, their effect is moderated by obstacles like limited access to technology, gaps in skills, and limited resources. A vital aspect of the framework is the role of strategic leadership in strengthening the relationships between ICT readiness and AI adoption. Strong leadership is hypothesized to help mitigate some difficulties caused by political instability and economic constraints. The chapter also examines how the perceived attributes of innovation, namely relative advantage and compatibility, moderate the impact of ICT readiness on AI uptake. These perceptions are particularly salient given the need for cost-effective solutions in resource-constrained Palestinian organizations.

Chapter Three

Methodology

3.1 Introduction

This chapter presents the methodological approach employed in this research study. It begins by outlining the research design and rationale, followed by a description of the selected population and sampling procedures. The chapter then details the data collection methods, including the instruments used and the procedures followed. Subsequently, it explains the data analysis techniques applied to interpret the gathered information. Ethical considerations and measures taken to ensure the study's validity and reliability are also addressed.

3.2 Research Design

Research design employs a quantitative and cross-sectional approach. This design choice is well-suited to the study's objectives and conceptual framework, which aim to examine the relationships between ICT readiness factors, AI adoption, the moderating effects of strategic leadership, and perceived attributes of innovation in Palestinian organizations. This design choice aligns with established methodologies in technology adoption research and allows for systematic empirical investigation of the relationships between variables (Li et al., 2022).

A quantitative approach is particularly appropriate for this study as it enables the testing of specific hypotheses and the examination of relationships between variables using statistical techniques (Huyler & McGill, 2019). Additionally, it is ideal as it allows for collecting and analyzing large amounts of data, facilitating objective measurement, and testing hypotheses (Creswell, 2010; Huyler & McGill, 2019). This method is widely used in technology adoption studies, allowing researchers to measure and analyze factors influencing the adoption of new technologies across various organizational contexts (Venkatesh et al., 2003).

The cross-sectional design, which involves collecting data at a single point in time, is particularly suitable for this study for several reasons. Firstly, it allows for an examination of the current state of AI adoption and ICT readiness in Palestinian organizations, providing a snapshot of the situation at a specific moment (Setia, 2016). This is crucial in the rapidly evolving field of AI and technology adoption, where conditions can change quickly (Sadashiv Jadhav, 2021b). Secondly, the cross-sectional approach is practical and feasible, allowing for data collection from a large number of organizations across different sectors within a reasonable timeframe and budget (Setia, 2016). This is particularly important given the study's aim to provide a comprehensive view of AI adoption across various organizational types and sizes.

Moreover, the cross-sectional design is well-suited to examining the moderating effects of strategic leadership and perceived attributes of innovation on the relationship between ICT readiness and AI adoption at a given point in time (Purwanto et al., 2022).It allows for the simultaneous measurement of all variables, enabling the researcher to analyze how these factors interact at a given point in time (Hayes, 2013). This is crucial for understanding the complex interplay between organizational characteristics, leadership, and innovation perceptions in the context of AI adoption.

The choice of a quantitative, cross-sectional design also aligns with the study's goal of producing generalizable results (Mohajan, 2020). By collecting data from a large, diverse sample of Palestinian organizations, the research can potentially yield findings that are applicable to a broader context, contributing to the wider body of knowledge on AI adoption in developing countries (Hart O. Awa & Ukoha, 2017). Additionally, this design facilitates comparisons between different types of organizations and sectors, potentially revealing essential patterns or differences in AI adoption and ICT readiness across the organizational landscape (Oliveira & Fraga Martins, 2011).

However, it's essential to acknowledge the limitations of this design. Cross-sectional nature means that causal relationships cannot be definitively established, as the study captures data at only one point in time (Levin, 2006). Additionally, the reliance on self-reported data through questionnaires may introduce some bias (Podsakoff et al., 2003). Despite these limitations, the quantitative, cross-sectional design remains the most appropriate choice for addressing the research questions and testing the hypotheses outlined in this study, providing a robust framework for examining the complex relationships between ICT readiness, AI adoption, strategic leadership, and perceived attributes of innovation in the Palestinian context.

3.3 Study Population

The target population for this study comprises Micro, Small, and Medium Enterprises (MSMEs) operating in Palestine, specifically in the West Bank. MSMEs play a crucial role in the Palestinian economy, representing over 98% of all businesses and contributing significantly to employment and economic growth (Alfoqahaa, 2018; Makkawi, 2023), with a total of 142,383 working establishments distributed across different sectors (MNE, 2017). For this research, the definition of MSMEs aligns with that used by the Palestine Central Bureau of Statistics (PCBS), which categorizes enterprises based on the number of employees (Alfoqahaa, 2018). This classification allows for a comprehensive examination of the diverse range of businesses that fall under the MSME category in Palestine.

The geographical scope of the study population covers both urban and rural areas in the West Bank. This inclusive approach ensures a representative sample that reflects the diverse economic landscape of Palestine.

In terms of ownership structure, the study population includes family-owned businesses, which constitute approximately 96% of Palestinian MSMEs (Sabri, 2008).

Additionally, the population encompasses enterprises owned by individuals, partnerships, and private corporations, reflecting the various legal forms of business organization in Palestine.

The study population also considers the gender dimension of MSME ownership and management. While male-owned businesses predominate, there is a growing segment of female entrepreneurs in the Palestinian MSME sector (Atyani Naser & Al-Haj , 2009; Sadeq et al., 2011). Including both male and female-owned MSMEs in the study population allows for a comprehensive analysis of potential gender-based differences in business operations and challenges.

The study's empirical context focused on executives, managers, IT managers, and policymakers overseeing operations within Palestinian MSMEs. The inclusion criteria were enterprises employing between 1 and 99 persons with diverse ownership structures in Palestine. Due to data availability and accessibility, the study primarily focused on MSMEs in the West Bank.

By focusing on this diverse and economically significant population of MSMEs in Palestine, the study aims to provide valuable insights into their operational characteristics, challenges, and growth potential. The findings derived from this population will contribute to the development of targeted policies and support mechanisms to enhance the resilience and competitiveness of Palestinian MSMEs.

3.4 Study Sample

In this cross-sectional, quantitative study of micro, small, and medium enterprises (MSMEs) in the West Bank of Palestine, the sample included participants, encompassing executives, managers, IT managers, policymakers, and employees, to provide a comprehensive perspective across various organizational levels. A stratified random sampling technique was employed to select an appropriate sample from this population (Schachtebeck et al., 2018;

Sharma, 2017). This method was chosen for its ability to capture the heterogeneity of the MSME sector while maintaining randomness within each stratum (Schachtebeck et al., 2018). The stratification was based on two key characteristics: enterprise size and economic sector. For enterprise size, the sample was divided into micro enterprises (1-4 employees), small enterprises (5-19 employees), and medium/large enterprises (20 or more employees), as classified by the Palestinian Central Bureau of Statistics (PCBS) (Alfoqahaa, 2018). The economic sector stratification was based on the estimated value of normal monthly production before the war 2023, including Industrial sector, Construction, Internal Trade, Transport and Storage, Telecommunication and Information, and Services(USAID report, 2023). This approach was particularly important in this case as it ensured that the sample adequately represented the various segments of the MSME population in terms of both size and economic importance, thereby enhancing the generalizability of the study's findings (Schachtebeck et al., 2018). By combining these two stratification criteria, the study could capture a more precise representation of these subgroups, which could have significant variations in their characteristics and challenges across different enterprise sizes and economic sectors in the West Bank.

The determination of the sample size was a critical step in the research design, balancing statistical power with practical constraints. Two methods were employed to calculate the appropriate sample size. First, using Krejcie and Morgan's (1970) table to determine the sample size from a given population, a sample of 384 MSMEs was initially targeted (Gerald et al., 2020). See Figure (3.1).

N	S	N	S	N	S	N	S	N	S
10	10	100	80	280	162	800	260	2800	338
15	14	110	86	290	165	850	265	3000	341
20	19	120	92	300	169	900	269	3500	246
25	24	130	97	320	175	950	274	4000	351
30	28	140	103	340	181	1000	278	4500	351
35	32	150	108	360	186	1100	285	5000	357
40	36	160	113	380	181	1200	291	6000	361
45	40	180	118	400	196	1300	297	7000	364
50	44	190	123	420	201	1400	302	8000	367
55	48	200	127	440	205	1500	306	9000	368
60	52	210	132	460	210	1600	310	10000	373
65	56	220	136	480	214	1700	313	15000	375
70	59	230	140	500	217	1800	317	20000	377
75	63	240	144	550	225	1900	320	30000	379
80	66	250	148	600	234	2000	322	40000	380
85	70	260	152	650	242	2200	327	50000	381
90	73	270	155	700	248	2400	331	75000	382
95	76	270	159	750	256	2600	335	100000	384

Note: N = number of population, S = number of sample

Figure (3.1): Sampling list Source (Krejcie & Morgan, 1970)

However, Cochran's formula was also applied to validate this sample size further. Cochran's method, developed by statistician William G. Cochran in 1963, is particularly useful for larger populations and yielded a similar result, suggesting a minimum sample size of 384 for a 95% confidence level and a 5% margin of error (Reza Asnafi et al., 21 C.E.).Where Cochran's formula is (Bartlett et al., 2001):

$$n = \frac{N \cdot Z^2 \cdot p \cdot (1-p)}{(N-1) \cdot E^2 + Z^2 \cdot p \cdot (1-p)}$$

Where:

- n is the sample size.
- N is the population size.
- Z is the Z-value (1.96 for 95% confidence level).
- p is the estimated proportion of the population (0.5 if unknown).
- E is the margin of error (alpha, 0.05).

Considering the potential for non-response and the need for robust data for structural equation modeling (SEM) analysis, the sample size was increased by 20% to 461. This adjustment was made to ensure that even with some non-responses, the final sample would be sufficient for the planned SEM analysis, which typically requires larger sample sizes for stable estimates (Baye & Gebeyehu Baye, 2023; Saini & Marketing, 2013). The decision to increase the sample size aligns with recommendations by Hair et al. (2010), who suggest that for SEM, a general rule is to have at least 10-20 times as many observations as variables.

The inclusion criteria for the study were carefully defined to ensure that the selected MSMEs were representative of the target population (Alfarizi et al., 2023). Eligible participants were required to be officially registered MSMEs or entrepreneurs operating in the West Bank of Palestine for at least one year. This criterion ensured that the businesses had sufficient operational experience to provide meaningful data. Additionally, the enterprises needed to have between 1 and 100 employees, aligning with the standard definition of MSMEs in the region. For individual participants, the inclusion criteria specified that they must be employed in one of the defined roles (executive, manager, IT manager, policymaker, and employee) within an eligible MSME.

Exclusion criteria were also established to maintain the focus and validity of the study. Businesses operating for less than a year were excluded due to their limited operational history. Large enterprises with more than 100 employees were also excluded as they fell outside the MSME definition. Furthermore, businesses in certain sectors, such as informal street vendors, were not included due to their unique operational characteristics that might skew the results. At the individual level, temporary or contract workers and those with less than six months of experience in their current role were excluded to ensure participants had sufficient knowledge of their organization's operations (Hoque & Islam, 2022). Also, MSMEs in the Gaza Strip were excluded, due to prevailing political circumstances.

In summary, the sampling approach taken in the present study was more thorough and relevant to the research goals and the operationalization of the target population. The use of a stratified random sampling method and sample size calculation using more than one method followed by clear-cut inclusion and exclusion criteria assured that the data would be both represented and adequate for the intended structural equation modeling analysis. This holistic representation of the level of analysis boosts the external validity and reliability of the study results. It provides a rational basis for comprehending the dynamics of MSMEs across the different organizational levels in the West Bank of Palestine.

3.5 Setting-The Palestinian MSMEs and Entrepreneurship

Micro Small and Medium Enterprises (MSMEs) play a crucial role in the Palestinian economy, significantly contributing to employment, economic growth, and innovation (Alfoqahaa, 2018; Makkawi, 2023; Morrar & Tawil, 2024; Sabri, 2008). In developing countries, MSMEs are a major source of income, a breeding ground for entrepreneurs, and a provider of employment (UNIDO, 2000), providing jobs for about 86% of the total workforce, and they contribute approximately 55% to the Palestinian Gross Domestic Product (GDP), underscoring their vital role in the local economy (Alfoqahaa, 2018; Makkawi, 2023; Sabri, 2010; Sabri, 2008). See Table (3.1).

Table (3.1): Estimated Value of normal monthly production before ware 2023 (US$ Million) by Sector in the West Bank: Source (USAID report, 2023).

Sector	Value of normal monthly production before ware 2023 (US$ million)	Percent
Industrial sector (Food and beverages ⁄ Construction ⁄ Stone and marble ⁄ Pharmaceuticals ⁄ Chemicals ⁄ Metal and engineering ⁄ Textiles and garments ⁄ Leather and shoes ⁄ Paper and packaging ⁄ Traditional and handicrafts ⁄ Plastic and rubber ⁄ Woodcraft and furniture).	485	35.13%
Construction	18.5	1.34%
Internal Trade	434	31.44%
Transport and Storage	12	0.87%
Telecommunication and Information	60	4.35%
Services (Education, health, finance, electricity, etc)	371	26.87%
Total	1,381	100%

In Palestine, MSMEs are defined based on the number of employees and annual turnover, as classified by the Palestinian Central Bureau of Statistics (PCBS). Micro enterprises have 1-4 employees, small enterprises have 5-19 employees, and medium enterprises have 20-49 employees, while those with 50 or more employees are considered large enterprises (Alfoqahaa, 2018) (Table 2).

Table (3.2): Classification criteria of enterprises in Palestine by number of employees -Source (Alfoqahaa, 2018).

Micro	**Small**	**Medium**	**Large**
1-4	5-19	20-49	50-over

According to the Palestinian Ministry of National Economy, economic establishments in Palestine are categorized into four groups based on size, with a total of 142,383 working establishments in 2017 distributed across different sectors, employing approximately 424,852 workers(MNE, 2017). Classification by size reveals that 88.6% are micro-establishments, 7.4% small, 2.6% medium-sized, and 1.4% large establishments (MNE, 2017). The geographical distribution shows that 70% of these enterprises are in the West Bank, while 30% are in the Gaza Strip (Alfoqahaa, 2018).

However, these enterprises face numerous challenges due to the difficult economic and political conditions in the region (Alfoqahaa, 2018; Sabri, 2010; Morrar & Tawil, 2024). Limited access to finance, restrictions on movement and trade, political instability, inadequate market access, and insufficient infrastructure are some of the significant hurdles they encounter. Despite these challenges, many Palestinian MSMEs have demonstrated resilience and adaptability (Hussain & Rizwan, 2024; MNE, 2017; Shahadat et al., 2023b).

While exact figures on innovation are scarce, several Palestinian MSMEs have emerged as leaders in entrepreneurship and innovation (Sabri, 2010; PITA, 2023). The Palestinian Information Technology Association of Companies (PITA) reports over 350 IT companies in Palestine, many of which are MSMEs focusing on software development, digital marketing, and IT services. The adoption of artificial intelligence (AI) among these MSMEs is still in its early stages (PITA, 2023). A recent study indicated that while interest in AI technologies is growing, implementation remains limited due to factors such as lack of expertise and financial constraints (Demaidi, 2023; ESCWA, 2022).

Despite these restrictions, the entrepreneurship and innovation sector in Palestine has been growing steadily in recent years (ESCWA, 2022; Nour, 2016). It helps reduce dependence on traditional sectors and promotes a knowledge-based economy while helping Palestine integrate into the global tech ecosystem, attracting foreign investment and partnerships (ESCWA, 2022; Nour, 2016; Tadj et al., 2023).This significant increase from previous years indicates a growing interest in entrepreneurship among Palestinians (PITA, 2023). The vast majority of startups specialize in e-commerce, followed by the education and health sectors; figure (3.3) shows the Sectors in which startups operate in Palestine. However, only a small percentage of startups (0.09 percent) use artificial intelligence, as confirmed by interviews with experts in technology incubators and accelerators (ESCWA, 2022); for instance, Mashvisor, a real estate analytics platform that uses AI to provide insights for US real estate investors, and Tawazon, an Arabic language mindfulness and meditation app that likely uses AI for personalized recommendations, figure (3.4) shows the list of startups that use artificial intelligence.

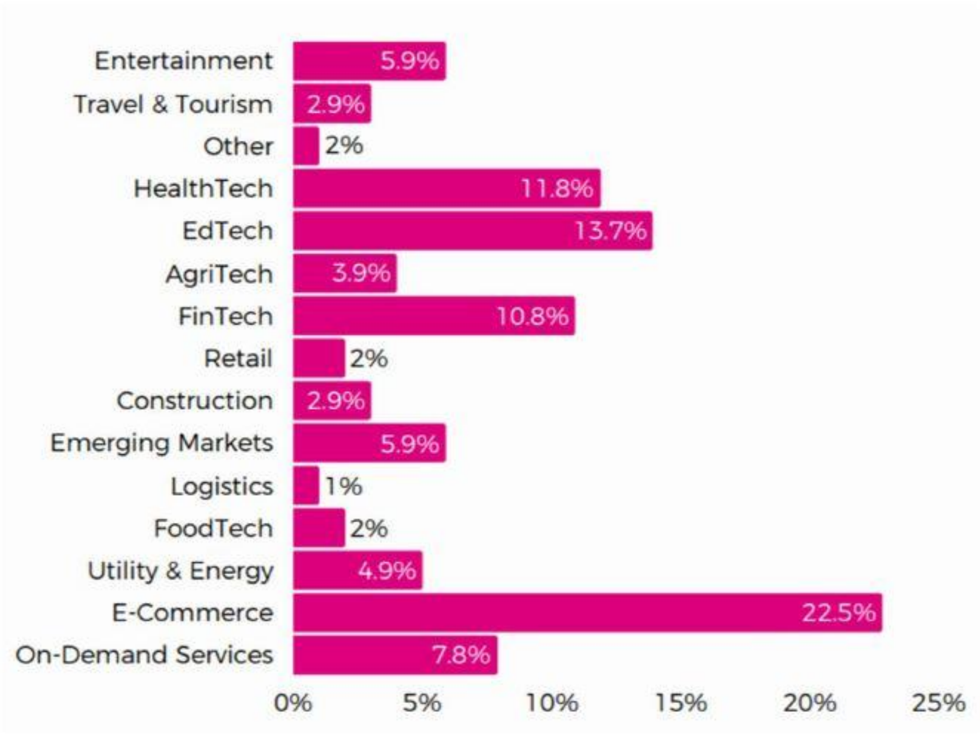

Figure (3.3): The Sectors in which startups operate in Palestine-Source (Polaris, 2022).

Figure (3.4): Artificial Intelligence Startups in Palestine -Source(ESCWA, 2022; Polaris, 2022)

The Palestinian startup scene has been attracting increasing attention from investors. In 2020, Palestinian tech companies raised approximately $60 million in funding (Morrar & Baba 2022). The Ibtikar Fund, Palestine's only venture capital firm, launched its first fund of $10 million in 2016 (Ibtikar Fund, 2023). More recently, Google announced an $8 million investment to support Israeli and Palestinian tech sectors, with $4 million earmarked for Palestinian enterprises (Mohammad Alnobani, 2024). Several initiatives and organizations are supporting the growth of the entrepreneurship sector, including incubators and accelerators like Gaza Sky Geeks, Birzeit University's Innovation and Entrepreneurship Unit, and the Rawabi Tech Hub Morrar & Baba 2022). The Innovative Private Sector Development Project, a $22 million initiative funded by the World Bank, works to address market failures in the Palestinian entrepreneurship ecosystem (Mohammad Alnobani, 2024). Additionally, Peleset Angels, an angel investor network supporting early-stage Palestinian startups, launched in August 2023(Mohammad Alnobani, 2024).

Moreover, the Palestinian education system plays a vital role in nurturing talent for the entrepreneurship and innovation sector (Istaitih & Mencet, 2014). Universities in Palestine produce more than 4,000 STEM graduates annually, with approximately 1,000 of these graduates going on to work for outsourced international companies (Mohammad Alnobani, 2024). Palestinians are known for their high proficiency in English, which is an asset in the global tech market (Mohammad Alnobani, 2024).

The number of graduates from Palestinian colleges and universities specializing in AI is still very small. Figure (3.5) shows that only 28 of the 13,939 graduates in the technology sector specialize in artificial intelligence between 2016 and 2021, and male graduates constitute a higher percentage than females, as their percentage is 60.7% compared to the value of 39.3% for females (ESCWA, 2022). The results highlight the low number of students specializing in artificial intelligence and the low participation of females in the specialization of artificial intelligence, in contrast to their participation at a very close percentage to males in the various technology sectors. The number of students specializing in artificial intelligence in Palestine has doubled by approximately 2.7 (as the number of students increased from 28 to 76 students)(ESCWA, 2022). However, the number of students enrolled in Palestinian universities specializing in artificial intelligence constitutes only 0.1% of the 104,499 enrolled in Palestinian universities and colleges from 2016 to 2021, which is a very small percentage (ESCWA, 2022).

The 2021 Stanford AI Index report revealed a total of 1,032 AI programs across the 27 EU countries (AI Index Report, 2021). The vast majority of AI programs in the EU are taught at the master's level, leading to a degree that equips students with strong workforce competencies. Germany leads other member states in offering the most specialized AI programs, followed by the Netherlands, France, and Sweden (AI Index Report, 2021).

In Palestine, 9% of Palestinian universities and colleges offer AI programs, and Figure (3.6) shows that Palestine offers 6 AI programs, a number that is very close to many EU countries. These programs constitute 2.6% of the 224 technology academic programs(ESCWA, 2022). The vast majority of these programs (83.3%) are master's programs, and there is no PhD program in Palestine yet specialized in AI (ESCWA, 2022). Palestine Technical University - Kadoorie, for instance, offers a bachelor's degree in Artificial Intelligence, aiming to equip students with skills in areas like computer vision, natural language processing, and robotics (PTUK, 2024). An-Najah National University has demonstrated excellence in international AI competitions, with its students securing top positions in the 2024 Global Hackathon for Quantum Computing and Artificial Intelligence, competing against 220 participants from 54 countries (Najah, 2024). There are also several initiatives and programs currently available in Palestine for students and graduates of Palestinian universities that focus on artificial intelligence, for example, the virtual course to learn the basics of cybersecurity provided by

Trend Micro, an American Japanese company for cybersecurity software, in partnership with the firm Girls in Tech(ESCWA, 2022; Michael Hill, 2020).

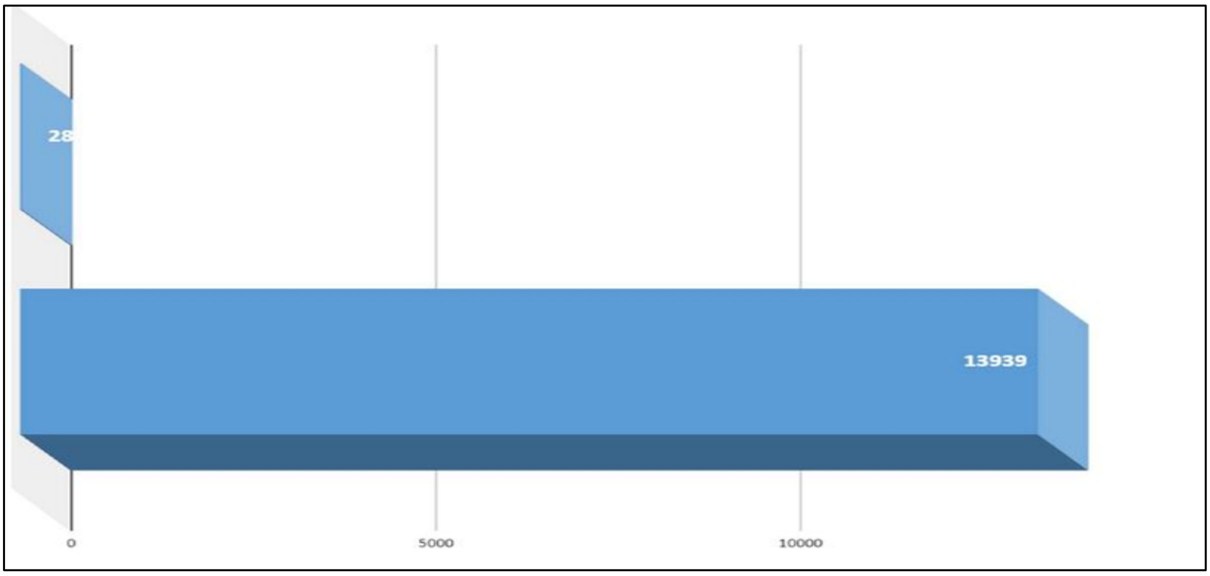

Figure (3.5): Number of graduates in the technology sector in Palestine (2016-2021)- Source (ESCWA, 2022)

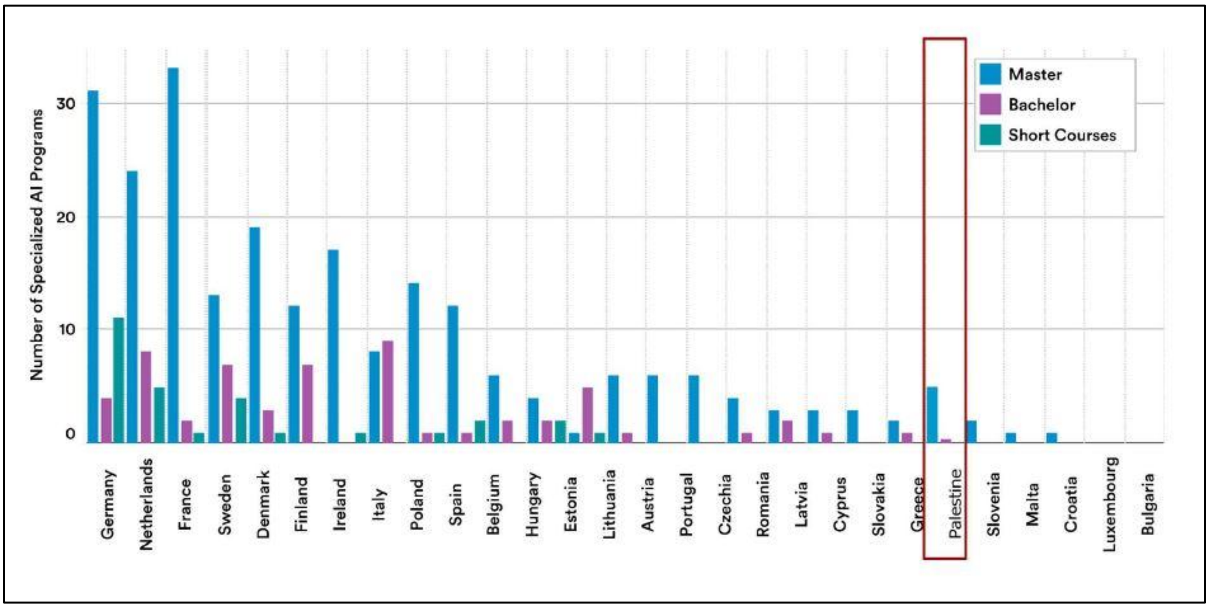

Figure (3.6): Academic programs specialized in AI in the European Union and Palestine- Source (ESCWA, 2022)

The Palestinian Ministry of Telecommunications and Information Technology has been promoting AI adoption in various sectors, and the Palestine Techno Park in Birzeit aims to foster innovation in emerging technologies, including AI (Palestine Techno Park, 2022). In conclusion, MSMEs and the entrepreneurship and innovation sector in Palestine, including its emerging AI initiatives, represent a beacon of hope for economic development and technological advancement. Despite facing significant challenges, Palestinian entrepreneurs and innovators continue to demonstrate resilience and creativity, contributing to the growth of a vibrant startup ecosystem. Nevertheless, the examination of MSMEs and entrepreneurship and innovation sector in the Gaza Strip will be excluded from this study owing to political circumstances.

3.6 Sampling Strategy and Sample Size Determination

In this section, we detail the sampling strategy and sample size determination employed in our study. A well-defined sampling strategy is crucial to ensure that the sample accurately represents the population, thereby enhancing the validity and reliability of the research findings. We employed a stratified random sampling method, which involves dividing the population into distinct subgroups and selecting samples from each, to achieve a representative sample. This approach allows for more precise and reliable results by ensuring that all relevant subgroups are adequately represented.

3.6.1 Calculation of Stratified Random Sample:

Step 1: Enterprise Size Stratification: Based on the given percentages (MNE, 2017):

- Micro enterprises (88.6% of 461): 461 × 0.886 = 408 (rounded down from 408.446)
- Small enterprises (7.4% of 461): 461 × 0.074 = 34 (rounded down from 34.114)
- Medium enterprises (2.6% of 461): 461 × 0.026 = 12 (rounded up from 11.986)
- Large enterprises (1.4% of 461): 461 × 0.014 = 7 (rounded up from 6.454)

Step 2: refer to Table (3.1), which has the Estimated Value of average monthly production before the 2023 war in Gaza by Sector in the West Bank and the percentage for each economic (USAID report, 2023):

- Sector Industrial sector: 35.12%,
- Construction: 1.34%,
- Internal Trade: 31.43%,
- Transport,
- Storage: 0.87%,
- Telecommunication and Information: 4.34%, and
- Services: 26.87%.

Step 3: Applying Proportions to Sample

Table (3.3): Stratified random sampling according to enterprise size and economic sector in the West Bank-Source Author

Economic Sector	**Micro Enterprises 1-4 employee**	**Small Enterprises 5-19 employee**	**Medium Enterprises 20-49 employee**	**Large Enterprises 50 over**	**Total MSMEs**
Industrial sector	143	12	4	3	162
Construction	5	1	0	0	6
Internal Trade	128	11	4	2	145
Transport and Storage	4	0	0	0	4
Telecommunication and Information	18	1	1	0	20
Services	110	9	3	2	124
Total	**408**	**34**	**12**	**7**	**461**

This stratified random sampling approach ensures that our sample accurately represents both the size distribution of MSMEs in Palestine and their distribution across different economic sectors. It allows for a more precise analysis of the MSME landscape in the West Bank, accounting for the unique characteristics of each size category and economic sector.

The inclusion of medium and large enterprises, albeit at a small percentage, provides a more comprehensive view of the business landscape in Palestine. This approach allows for potential comparative analysis between different enterprise sizes across various sectors.

3.7 Study Instruments

In this study, a structured digital survey questionnaire was developed as the primary data collection instrument. The questionnaire was initially designed in English, drawing from established scales in the relevant literature. To ensure content validity, the instrument was reviewed by a panel of experts. Following their feedback, necessary modifications were made to enhance clarity and relevance. A total of 1,500 respondents from Palestinian micro, small, and medium enterprises (MSMEs) were invited to participate in the survey, and 520 completed the electronic questionnaire. This response rate exceeds the calculated sample size of 461, ensuring robust data collection. The data collection period spanned from the end of October 2024 to the end of November 2024.

Since Arabic is the most spoken language in Palestine, the questionnaire was then translated into Arabic using the back-translation method to ensure semantic equivalence (Brislin, 1970). This was done by a bilingual expert translating from English into Arabic and a different bilingual expert translating back to English. Discrepancies were discussed and resolved to ensure accuracy and cultural appropriateness. The Arabic version was then pilot tested for its understandability and contextualization by 5 MSME managers. Few changes were made after the pilot study in order to enhance the reliability and validity of the instrument (van Teijlingen & Hundley, 2002). The resulting questionnaire was organized into sections, including demographic information, multiple items using a Likert scale to measure the core constructs, and open-ended items to provide additional insight into the responses. This rigorous development and translation process made sure that the instrument was comparable in both language and culture for the target population of the West Bank of Palestine.

3.7.1 Instruments Layout

The study employs survey data collected from Small and Medium Enterprises (SMEs) across various sectors, including entrepreneurship and innovation, in the West Bank of Palestine to test the study hypotheses. The questionnaire is composed of three main sections, each designed to capture specific data related to the participants:

Section One: provide clear instructions about the research and researcher, and how the participants navigate the questionnaire.

Section Two: The second section of the structured questionnaire illustrates the respondents' and firms' profiles to collect socio-demographic data. The respondents' profiles include:

- Gender (Male or Female),
- Position (General Manager CEO/Director, Production Executive/Manager, Marketing/Purchasing/Sales Executive/Manager, Senior Finance and HR Managers, IT Application Manager, IT Infrastructure Manager, IT development manager, and others),
- Managerial experience is categorized into four ranges: 1-5 years, 5-10 years, 10-15 years, or more than 15 years,
- Age of respondents,
- Educational level (Secondary school, bachelor’s degree, master’s degree, Doctorate, Other), and
- Experience in AI (None, less than 2 years, 2 years to less than 5 years, 5 years or more).

The second part of the second section covers the firm's profile, which includes:

- Size based on the number of personnel within the organization, categorized into four groups: (1-4, 5-19, 20-49, 50 over),
- Organization/firm sector (Industrial sector, Telecommunication and Information, Transport and Storage, Construction, Internal trade/ E-commerce, Education, and Marketing, Financial, Services/Banking, Healthcare, Electricity, Other), and

Section Three: 37 indicators will be used under 8 dimensions to measure the research variables as shown in Table (3.4). In this section, the researcher developed a comprehensive questionnaire comprising five distinct parts, each drawing upon established studies to ensure content validity and reliability. This multi-faceted approach allows for a robust examination of the relationships between AI adoption and implementation in the Palestinian context, considering factors like ICT readiness (infrastructure, hardware, information/system, people/human resources), strategic leadership, and perceived attributes of innovation (Relative advantage/Compatibility).

Relative Advantage Construct: The first part adopts indicators for measuring relative advantage from Sadashiv Jadhav (2021b) and Moore& Benbasat (1991) It is essential as it captures the degree to which an innovation is perceived as better than the idea it supersedes. The relative advantage indicators will provide insights into how professionals view the benefits of adopting new practices or technologies compared to existing methods. This construct is crucial in understanding the likelihood of innovation adoption, as innovations with a higher perceived relative advantage are more likely to be adopted and implemented in different sectors.

Compatibility Construct: The second includes measures of compatibility based on the research reported in Sadashiv Jadhav (2021a). This is an essential element because it measures the extent to which an innovation is perceived to be compatible with the values, past experiences, and needs of potential adopters in all sectors. Related and oriented towards the compatibility of a technology or practice with the existing cultures, processes, preferences, or behaviors of individual workers, the compatibility indicators will tell us how well it is likely to perform and be adopted. This is a crucial construct for predicting adoption by industry, with innovations that are more compatible with existing systems and values being likely to be adopted with less resistance. Researchers and practitioners will use compatibility measures to develop a deeper understanding of the possible barriers or facilitators to adopt innovation in their organizational contexts, encompassing manufacturing, education, finance, and high-tech sectors.

AI Adoption indicators: Dimension three includes indicators of AI adoption, based on Gupta & Yang (2024) and Almaiah, Alfaisal, et al. (2022b). This element is important because it measures how widely artificial intelligence technologies are being adopted and deployed across industries and enterprises. The indicators will serve to shed light on what encourages or inhibits the adoption of these systems, such as the preparation of the company. Exploring these issues aids stakeholders in understanding what is limiting and how they could capitalize on opportunities associated with the adoption of AI, which in turn may allow for swifter, more effective strategies for implementation and, ultimately, better outcomes across an array of organizational contexts including professional services, manufacturing, finance and technology sectors among others.

ICT Readiness assessment: ICT readiness indicators in this domain are derived from the study done by Chanyagorn & Kungwannarongkun (2011). This component is critical because it evaluates an organization's readiness to use Information and Communication Technologies throughout its scope. The ICT readiness construct is an aggregate of four factors, namely: ICT Infrastructure (concerning underlying technology), ICT Hardware (availability and quality of physical ICT devices), ICT Information and Systems (software applications and information management systems), and ICT People and Human Resources (staff skills and competencies in using ICT). All of these together display the level of an organization in terms of ICT readiness, the current status of ICT preparedness, and the area where the ICT is to be improved or needs more investment. Such a construct is central to determining the potential of successful adoption and implementation of ICT among the sectors since the higher the levels of ICT readiness within the organization, the greater the likelihood that new technologies will be adopted and effectively implemented. By focusing on these aspects, researchers and practitioners would know the challenges and opportunities that can be found in adopting ICT, potentially bettering the precision of strategies for increasing ICT capabilities in many organizational contexts.

Strategic Leadership Construct: This section measures strategic leadership using indicators from Fourie & Jacob Fourie (2007). It assesses leaders' ability to create and implement long-term strategies for innovation, growth, and competitive advantage across various sectors. The construct includes elements like visionary thinking, strategic decision-making, fostering organizational learning, and managing change. These indicators provide insights into how leadership influences an organization's adaptability, resource allocation, and goal alignment. By examining these factors, researchers and practitioners can understand the impact of strategic leadership on organizational outcomes, including innovation adoption and business success, potentially leading to improved leadership development and organizational strategies across industries.

This structured and detailed approach to questionnaire development will enable the researcher to collect meaningful data that can inform insights into the interplay between various factors influencing AI adoption in Palestinian organizations.

Table (3.4): Items for Measuring Constructs

Construct	Construct Type	Indicators /Categories	Source/ Author(s)
AI adoption	Dependent Variable	4 indicators	(Almaiah, Alfaisal, et al., 2022b; Gupta & Yang, 2024)
ICT readiness	Independent Variable	15 indicators are used under 4 categories including :(a) ICT infrastructure factor, (b) ICT hardware factor, (c) ICT software and information system factor, and(d) ICT human resources factor	(Chanyagorn & Kungwannarongkun, 2011)
Strategic Leadership	Moderator Variable	7 indicators	(Fourie & Jacob Fourie, 2007)
Perceived attributes of innovation (Relative Advantage)	Moderator Variable	11 indicators	(Moore & Benbasat, 1991; Sadashiv Jadhav, 2021a)
Perceived attributes of innovation (Compatibility)	Moderator Variable	4 indicators	(Sadashiv Jadhav, 2021b)

3.7.2 Instrument Validity and Reliability

Validity, as defined by (n. Kerlinger & Amón, 1976), pertains to the extent to which an instrument accurately measures its intended construct. It pertains to the precision and suitability of the instrument in assessing the constructs that the researcher intends to investigate. Content validity for this research was established through the involvement of a panel of experts.

The researcher consulted five experts to evaluate the questionnaire's content validity. These comprised two specialists in strategic management, two academic experts in research methodology, including a statistician, and one expert in AI. The experts offered critiques regarding the organization, substance, and lucidity of the items in the questionnaire. Their recommendations were meticulously incorporated to enhance the instrument, guaranteeing its precise measurement of the intended variables across various domains.

The construct validity of the questionnaire was evaluated using Pearson Correlation tests, which are statistical measures designed to assess the strength and direction of relationships between variables. In this context, these tests were employed to examine how well individual items within each domain of the questionnaire correlated with the overall construct they were intended to measure. A high correlation coefficient (closer to 1 or -1) would indicate that the item effectively measures the intended construct. In contrast, a low correlation (closer to 0) might suggest that the item is not adequately capturing the concept. This process helps researchers refine their questionnaires by identifying items that may not be effectively contributing to the measurement of the intended construct, thereby improving the overall validity of the instrument (Schober & Schwarte, 2018).

The results of the Pearson Correlation Test show the strength and significance of the correlations across different domains in the study. Most of the items exhibited significant positive correlations, reinforcing the validity of the questionnaire.

Reliability in research refers to consistency, stability, and repeatability of measurements or results over time and across different conditions (Kalpande & Toke, 2022). It is a crucial aspect of any research instrument, ensuring that the tool consistently measures what it's intended to measure, regardless of when or how often it's used. Reliability is typically assessed through various statistical methods, with Cronbach's alpha being one of the most used (Kalpande & Toke, 2022; Sujati et al., 2020). Cronbach's alpha provides a measure of internal consistency, indicating how closely related a set of items are as a group. It's calculated on a scale from 0 to 1, with values above 0.70 generally considered acceptable, above 0.80 good, and above 0.90 excellent. Other methods to assess reliability include test-retest reliability (measuring consistency over time), inter-rater reliability (consistency between different raters), and split-half reliability (consistency between two halves of a test). In practice, researchers often use a combination of these methods to ensure a comprehensive assessment of their instrument's reliability. For instance, they might calculate Cronbach's alpha for each subscale of a questionnaire, conduct a test-retest analysis with a subset of participants, and potentially have multiple raters score responses to check for inter-rater reliability. This multi-faceted approach helps to establish a robust understanding of the instrument's reliability, ensuring that the data collected is consistent and trustworthy for further analysis and interpretation (Kalpande & Toke, 2022; Sujati et al., 2020).

The alpha coefficient has been calculated for each of the key variables in the study—AI adoption, ICT readiness, Strategic leadership, and perceived attributes of innovation—to ensure the reliability of the scales. If the results indicate low reliability, further investigation into individual items will be conducted, such as removing or revising poorly performing items. This will ensure that the questionnaire provides reliable and accurate data for subsequent analysis.

The results of Cronbach’s alpha reliability test for each domain in the study indicate excellent overall reliability. No areas require further review to address the lower alpha values.

3.8 Ethical Consideration

Research at Arab American University is based on ethical standards with the utmost protection of participants. This study was approved by the Institutional Review Board (IRB), which ensured the rights and confidentiality of subjects. All participants received a consent letter with an IRB approval form " R-2024/A/159/N" including the objective of the study, their decision to take part entirely up to them, and protection of their confidentiality.

A relevant information sheet enables participants to make an informed decision about their participation. All personally identifiable information was kept confidential, and the data was stored securely and was accessible only to those who requested it. The study observes key considerations of non-maleficence, such as not including sensitive questions and reducing possible risks to participants. Overall, the research evidence displays a strong commitment to ethics and the well-being of its participants.

3.9 Data Collection

The data collection process for this cross-sectional quantitative study was designed to capture a comprehensive snapshot of the MSMEs landscape in the West Bank of Palestine at a single point in time. A structured questionnaire, the primary data collection instrument, was administered to a stratified random sample of MSMEs, targeting executives, managers, IT managers, policymakers, and employees. To accommodate the diverse nature of the MSMEs sector, a mixed-mode approach was employed, combining online surveys and in-person data collection. The online survey was distributed via email and professional networking platforms, while on-site data collection was conducted at business locations. The questionnaire, available in both Arabic and English, consisted primarily of closed-ended questions using Likert scales to measure critical constructs. Demographic information was also collected to enable subgroup analyses. The data collection period was strictly limited to a six-week window to maintain the cross-sectional nature of the study, ensuring all responses reflected the same temporal context. To maximize response rates and minimize non-response bias, follow-up reminders were sent at regular intervals. Data collection was conducted simultaneously across different geographical areas and industry sectors to control for potential confounding variables. This approach allowed for a comprehensive, quantitative assessment of the MSMEs sector, capturing variations across different organizational levels and business characteristics while maintaining the integrity of the cross-sectional design.

3.10 Data Analysis

This study's data analysis will employ various quantitative techniques to thoroughly comprehend the relationships among the key variables (Mohajan, 2020). The variables will be examined using descriptive and inferential statistical techniques, encompassing reliability testing, correlation analysis, and structural equation modeling (SEM).

Data Cleaning: Check for missing values, outliers, and errors in data entry. Address these issues appropriately, such as through imputation or removal of problematic cases.

Descriptive Analysis: Descriptive statistics, including means, standard deviations, and frequencies, were calculated for all variables. These analyses provided an overview of the sample characteristics and distribution of responses. Demographic information was summarized to describe the profile of participating MSMEs and respondents. Histograms and box plots were used to inspect the distribution of key variables visually. This initial analysis helped in understanding the general trends and patterns in the data, as suggested by Altukhi & Aljohani (2024).

Outlier Analysis: Outlier analysis is a statistical technique for identifying and examining data points that significantly deviate from the majority of observations in a dataset. Box plots and statistical tests are used to detect outliers (Goldfarb et al., 2020).

Normality Assessment: Examine the normal distribution of variables using descriptive statistics, histograms, and normality tests (e.g., Shapiro-Wilk test) to ensure the data meets assumptions for parametric tests (Mishra et al., 2019).

Reliability Analysis: The reliability of the measurement scales was assessed using Cronbach's alpha coefficient. Following Nunnally and Bernstein's (1994) recommendations, a threshold of 0.7 was used to indicate acceptable internal consistency (Kalpande & Toke, 2022).

Validity Analysis: Validity was assessed through several methods. Content validity was established during the instrument development phase through expert review and pilot testing.

Construct validity was evaluated using exploratory factor analysis (EFA) and confirmatory factor analysis (CFA). EFA was conducted using principal axis factoring with oblique rotation to examine the underlying factor structure. CFA was then performed to confirm the measurement model. Convergent validity was assessed using average variance extracted (AVE), with values above 0.5 considered acceptable (Fornell & Larcker, 1981). Discriminate validity was evaluated by comparing the square root of AVE with inter-construct correlations(Kalpande & Toke, 2022).

Correlation Analysis (Regression analysis): Pearson correlation coefficients were calculated to examine the bivariate relationships between key variables. This analysis provided initial insights into the strength and direction of associations among constructs. The correlation matrix was also used to check for potential multicollinearity issues, with correlations above 0.8 flagged for further investigation. Additionally, variance inflation factors (VIF) were computed to further assess multicollinearity in the structural model (Gogtay & Thatte, 2017).

Structural Equation Modeling (SEM): The primary analytical technique for testing the hypothesized relationships will be SEM. SEM is a multivariate statistical analysis method that allows researchers to examine the structural relationships between multiple variables simultaneously. The advantage of SEM is its ability to handle complex models with multiple mediating, moderating, and dependent variables, as well as account for measurement error (Sujati et al., 2020). SEM will be conducted using AMOS or SmartPLS software, depending on the model's complexity and the sample size.

Measurement Model: The measurement model was evaluated using CFA to assess the relationships between constructs and their indicators. Factor loadings, composite reliability, and AVE were examined to ensure convergent validity. Modification indices were consulted to identify potential improvements in model fit, with theoretical justification guiding any modifications. The final measurement model provided the basis for the structural model analysis (Sujati et al., 2020).

Structural Model: Following the validation of the measurement model, the structural model will be assessed to investigate the proposed relationships between ICT readiness and AI adoption. The analysis will also examine the moderating influence of strategic leadership and perceived innovation attributes in these relationships (Sujati et al., 2020).

Hypotheses Testing: The significance of the direct, indirect, and total effects in the structural model will be examined using the standardized regression weights (beta coefficients) and p-values (Morrow et al., 2022).

The results from these analyses will help to confirm or reject the hypotheses, offering a detailed understanding of how ICT readiness for AI adoption through the moderating role of strategic leadership and perceived attributes of innovation (relative advantage/compatibility) in Palestinian organizations.

3.11 Chapter Three Summary

The research employs a cross-sectional, quantitative approach to examine the implementation of artificial intelligence technologies in West Bank-based Palestinian enterprises. The investigation targets a diverse group of stakeholders, including senior management, staff members, and decision-makers involved in AI integration efforts. A comprehensive literature review informed the development of the study's theoretical framework, which was further enhanced by primary data gathered through an online self-administered survey. The research utilizes structural equation modeling (SEM) to analyze the complex relationships between variables. This sophisticated statistical technique allows for the simultaneous evaluation of the measurement model's validity and the testing of hypothesized relationships. The study explores explicitly how Information and Communication Technology

(ICT) readiness influences AI adoption while considering the potential moderating effects of leadership strategies and perceived innovation characteristics. The study's geographical scope is limited to the West Bank region of Palestine, excluding Gaza Strip organizations. Rigorous statistical procedures were applied to ensure thorough analysis and validation of the research constructs, providing a robust foundation for the study's findings and conclusions.

Chapter Four

Result

1.1 Introduction

This chapter presents the study's findings and analysis. First, it presents descriptive statistics about the sample and the study's main variables. Second, it provides key measures to evaluate the measurement model's overall reliability and validity assessment. Finally, it includes hypothesis testing results using PLS-SEM and SPSS, offering a detailed overview of the data analysis process.

1.2 Characteristics of Respondents

Table (4.1) summarizes the respondents' demographic characteristics for a total of 520 participants who were surveyed in this study. Results revealed that 67.1% of the respondents were male (349 participants), while 32.9% were female (171 participants). For **age** distribution, 25.8% of respondents were between 18 to 30 years, 24.2% were between 31 to 44 years, 20.2% were between 45 to 60 years, and 29.8% were over 60 years old. The sample represented a variety of **job descriptions**, including IT Development Managers (9.4%), IT Infrastructure Managers (13.7%), IT Application Managers (11.9%), Senior Finance and HR Managers (15.4%), Marketing/Purchasing/Sales Executives/Managers (10.6%), Production Executives/Managers (12.9%), General Managers/CEOs/Directors (10.6%), and others (15.6%). In terms of **managerial experience**, 29.0% had 1-5 years of experience, 24.0% had 5-10 years, 22.5% had 10-15 years, and 24.4% had more than 15 years.

Educationally, participants' qualifications ranged from secondary school (17.7%) to bachelor's degrees (20.4%), master's degrees (19.6%), doctorate degrees (19.2%), and other qualifications (23.1%). Concerning **years of experience** in implementing or using artificial intelligence technologies, 29.4% reported no experience, 22.9% had less than 2 years of experience, 23.3% had 2 to less than 5 years, and 24.4% had 5 years or more. The **industry** representation included the manufacturing sector (32.7%), telecommunication and information (4.4%), transport and storage (1.0%), construction (1.7%), internal trade (32.3%), and services (27.9%). Finally, firms size (Number of employees), 78.7% have 1-4 employees, 13.5% have 5-19 employees, 5.8% have 20-49 employees, and 2.1% employing over 50 individuals.

Table (4.1) Demographic Characteristics Analysis

Variables	Options	Frequency	Valid Percentage%
Gender	Male	349	67.1
	Female	171	32.9
Age	18 to 30	134	25.8
	31 to 44	126	24.2
	45 to 60	105	20.2
	More than 60	155	29.8
Job Description	IT development manager	49	9.4
	IT Infrastructure Manager	71	13.7
	IT Application Manager	62	11.9
	Senior Finance and HR Managers	80	15.4
	Marketing/Purchasing/Sales Executive/Manager	55	10.6
	Production Executive/Manager	67	12.9
	General Manager CEO/Director	55	10.6
	Others	81	15.6
Managerial experience	1-5 years	151	29.0
	5-10 years	125	24.0
	10-15 years	117	22.5
	more than 15 years	127	24.4
Educational level	Secondary school	92	17.7
	Bachelor’s degree	106	20.4
	Master’s degree	102	19.6
	Doctorate degrees	100	19.2
	Others	120	23.1
Years of experience	None	153	29.4
	Less than 2 years	119	22.9
	2 years to less than 5 years	121	23.3
	5 years or more	127	24.4
Firm Sector	Industrial sector	170	32.7
	Telecommunication and Information	23	4.4
	Transport and Storage	5	1.0
	Construction	9	1.7
	Internal Trade	168	32.3

	Services	145	27.9
Number of employees	1-4	409	78.7
	5-19	70	13.5
	20-49	30	5.8
	50 over	11	2.1
	Total	520	100%

1.3 Descriptive Statistics

This section presents measures of central tendency (mean) and dispersion (standard deviation) for the key variables of the research model. This includes ICT readiness factors, strategic leadership indicators, perceived attributes of innovation, and AI adoption levels. A 5-point Likert scale was used, with scores from 1 to 2.9 indicating a "low" level of agreement, 3 to 3.9 reflecting a "moderate" level, and 4 to 5 representing a "high" level of agreement. The results in Tables (4.2 to 4.5) provide the following insights:

1.3.1 ICT Readiness (ICT-R)

Results presented in Table 4.2 reveal a strong level of ICT Readiness (ICT-R) with an overall mean of 4.903 and a standard deviation of 0.503. Negative responses were slightly lower at 1.75%, while positive responses constituted 97.47% and 0.78% neutral responses as indicated by the survey results in Table 4.2.

ICT Infrastructure (ICT-I) achieved an overall mean score of 4.906 with a standard deviation of 0.485. Individual items Q16, Q17, and Q18 exhibited strong agreement, with mean scores above 4.910 and positive responses exceeding 97%. Although Q19 had a slightly lower mean of 4.890, it still reflected high agreement with 97.31% positive responses and minimal neutral or negative feedback.

ICT Hardware (ICT-H) showed robust performance, with an overall mean score of 4.899 and a standard deviation of 0.518. Items Q20, Q21, and Q22 consistently scored above 4.890, with positive responses exceeding 96%. Q20 demonstrated the highest level of agreement at 97.69%, indicating significant satisfaction with the organization's hardware capabilities.

ICT Software (ICT-S) achieved an overall mean score of 4.904 with a standard deviation of 0.502. Items Q23 through Q26 recorded positive responses above 96%, with Q25 achieving the highest mean score of 4.919 and 97.50% positive feedback. These results reflect strong satisfaction with the organization's software systems.

ICT People and Human Resources (ICT-P) demonstrated similarly high agreement, with an overall mean of 4.904 and a standard deviation of 0.503. Items Q27 and Q29 achieved the highest scores, both with a mean of 4.921 and positive responses exceeding 97%. Items Q28 and Q30 also showed strong agreement, with positive responses above 97% and minimal neutral or negative feedback.

Overall, these results highlight consistently strong agreement across all dimensions of ICT readiness, including infrastructure, hardware, software, and human resources. The high mean scores and low percentages of negative and neutral responses underscore the organization's robust capacity to leverage ICT effectively to achieve its objectives.

Table (4.2): ICT Readiness Dimensions and Indicators: Mean, Standard Deviation, and Percentage

Construct	Q.#	Mean	Std.	% of Negative response	% of Neutral	% of Positive response	Level of Agreement
ICT-I	Q16	4.913	0.463	1.54%	0.96%	97.50%	High
	Q17	4.910	0.466	1.54%	0.96%	97.50%	High
	Q18	4.910	0.458	1.54%	0.58%	97.88%	High
	Q19	4.890	0.553	2.12%	0.58%	97.31%	High
	Overall	4.906	0.485	1.68%	0.77%	97.55%	High
ICT-H	Q20	4.902	0.527	2.12%	0.19%	97.69%	High
	Q21	4.896	0.501	1.54%	1.54%	96.92%	High
	Q22	4.898	0.526	1.92%	0.58%	97.50%	High
	Overall	4.899	0.518	1.86%	0.77%	97.37%	High
ICT-S	Q23	4.898	0.540	2.12%	0.19%	97.69%	High
	Q24	4.906	0.501	1.54%	0.77%	97.69%	High

	Q25	4.919	0.445	1.54%	0.96%	97.50%	High
	Q26	4.892	0.523	1.92%	1.35%	96.73%	High
	Overall	4.904	0.502	1.78%	0.82%	97.40%	High
ICT-P	Q27	4.921	0.451	1.35%	0.77%	97.88%	High
	Q28	4.887	0.589	2.50%	0.19%	97.31%	High
	Q29	4.921	0.407	0.58%	1.73%	97.69%	High
	Q30	4.887	0.573	2.31%	0.38%	97.31%	High
	Overall	4.904	0.505	1.68%	0.77%	97.55%	High
ICT-R		4.903	0.503	1.75%	0.78%	97.47%	High

1.3.2 AI Adoption (AI-A)

The construct AI-A achieved a mean of 4.900 and a standard deviation of 0.501, reflecting a high level of agreement. Negative responses were slightly lower at 1.63%, while positive responses constituted 97.21%, with minimal neutral responses. The indicators result of AI-A indicate high levels of agreement across all evaluated indicators as presented in Table 4.3, with mean scores ranging from 4.894 to 4.910. Q12 achieved a mean of 4.894, with 97.31% positive responses, 0.77% neutral, and only 1.92% negative feedback, reflecting strong satisfaction with the adoption of AI technologies. Similarly, Q13 recorded a slightly higher mean of 4.902, with 97.31% positive responses, 0.96% neutral, and 1.73% negative feedback. Q14 also scored a mean of 4.894, with 96.92% positive responses, 1.15% neutral, and 1.92% negative feedback, indicating robust agreement on the effectiveness of AI integration. Finally, Q15 achieved the highest mean score of 4.910, with 97.31% positive responses, 1.73% neutral, and just 0.96% negative feedback, emphasizing the strong alignment and acceptance of AI adoption practices. These results demonstrate high levels of satisfaction with AI adoption across all constructs, highlighting its effective integration and alignment within the organizational context.

Table (4.3): AI Adoption Indicators: Mean, Standard Deviation, and Percentage

Construct	Q.#	Mean	Std.	% of Negative response	% of Neutral	% of Positive response	Level of Agreement
AI-A	Q12	4.894	0.533	1.92%	0.77%	97.31%	High
	Q13	4.902	0.497	1.73%	0.96%	97.31%	High
	Q14	4.894	0.518	1.92%	1.15%	96.92%	High
	Q15	4.910	0.458	0.96%	1.73%	97.31%	High
	Overall	4.900	0.501	1.63%	1.15%	97.21%	High

1.3.3 Perceived Attributes of Innovation (PAI)

Table 4.4 reveals a strong level of agreement with PAI, with a mean score of 4.904 and a standard deviation of 0.495. The proportion of negative responses was 1.63%, while positive responses dominated at 97.57%, with 0.8% neutral responses recorded. The survey results indicate high levels of agreement for the constructs within the perceived attributes of innovation (PAI) framework, specifically for Relative Advantage (RA) and Compatibility (CO).

The Relative Advantage (RA) construct demonstrated a high level of agreement, with a mean of 4.907 and a standard deviation of 0.485. Negative responses accounted for 1.57%, and positive responses were at 97.69%, with 0.74% neutral responses. Individual items (Q1 to Q7) consistently scored above 4.883, with positive responses exceeding 96% for all questions. Notably, Q1 achieved the highest mean of 4.946, with 98.65% positive responses and only 0.38% negative feedback, highlighting the perceived significant benefits of adopting innovation.

For Compatibility (CO), the overall mean score was 4.900 with a standard deviation of 0.512, indicating similarly strong agreement. Items, Q8 through Q11, showed consistently high scores, with positive responses ranging from 96.92% to 97.88%. Q9 achieved the highest mean of 4.915, with only 1.35% negative responses, emphasizing alignment with organizational practices.

The results suggest a consistently high level of agreement among respondents across all items and constructs, with very low variability in responses (as evidenced by the low standard deviations). The overwhelmingly positive responses highlight strong perceptions of reward attributes and collaboration within the study population. These findings indicate that participants generally agree on the effectiveness of the reward attributes and collaboration dimensions measured in this study.

Table (4.4): Perceived attributes of innovation and Indicators: Mean, Standard Deviation, and Percentage

Construct	Q.#	Mean	Std.	% of Negative response	% of Neutral	% of Positive response	Level of Agreement
RA	Q1	4.946	0.341	0.38%	0.96%	98.65%	High
	Q2	4.915	0.469	1.54%	0.77%	97.69%	High
	Q3	4.885	0.554	2.12%	0.38%	97.50%	High
	Q4	4.912	0.493	1.35%	0.58%	98.08%	High
	Q5	4.904	0.479	1.54%	0.77%	97.69%	High
	Q6	4.902	0.504	1.73%	0.77%	97.50%	High
	Q7	4.883	0.555	2.31%	0.96%	96.73%	High
	Overall	4.907	0.485	1.57%	0.74%	97.69%	High
CO	Q8	4.890	0.567	2.31%	0.77%	96.92%	High
	Q9	4.915	0.457	1.35%	0.77%	97.88%	High
	Q10	4.908	0.476	1.15%	1.35%	97.50%	High
	Q11	4.888	0.547	2.12%	0.77%	97.12%	High
	Overall	4.900	0.512	1.73%	0.91%	97.36%	High
PAI		4.904	0.495	1.63%	0.80%	97.57%	High

1.3.4 Strategic Leadership (SL)

The Strategic Leadership (SL) mean score was 4.896, with a standard deviation of 0.517, indicating a high level of agreement. The survey results for SL demonstrated consistently high levels of agreement across all evaluated indicators as shown in Table 4.5, with mean scores ranging from 4.890 to 4.906, indicating strong satisfaction among respondents with strategic leadership practices. Q31 achieved a mean score of 4.896, with 97.31% positive responses, 0.77% neutral, and only 1.92% negative feedback, reflecting strong alignment with leadership strategies. Similarly, Q32 scored a mean of 4.890, with 97.12% positive responses, 0.96% neutral, and 1.92% negative feedback. Q33 recorded a mean of 4.894, with 97.12% positive responses and minimal neutral (1.15%) and negative (1.73%) feedback. Q34 and Q35 both scored 4.898, with Q34 achieving 96.92% positive responses and Q35 receiving 97.50% positive feedback, with minimal neutral and negative responses in both cases. Q36 maintained strong agreement with a mean of 4.892, with 97.31% positive responses, 0.77% neutral, and 1.92% negative feedback. Lastly, Q37 achieved the highest agreement, with a mean score of 4.906 and 97.88% positive responses, while neutral and negative responses were limited to 0.58% and 1.54%, respectively. Overall, these results highlight the effectiveness of strategic leadership within the organization, with consistently high satisfaction levels and minimal neutral or negative responses, emphasizing strong support for current leadership practices.

Table (4.5): Strategic Leadership Indicators: Mean, Standard Deviation, and Percentage

Construct	**Q.#**	**Mean**	**Std.**	**% of Negative response**	**% of Neutral**	**% of Positive response**	**Level of Agreement**
SL	Q31	4.896	0.520	1.92%	0.77%	97.31%	High
	Q32	4.890	0.550	1.92%	0.96%	97.12%	High
	Q33	4.894	0.507	1.73%	1.15%	97.12%	High
	Q34	4.898	0.488	1.54%	1.54%	96.92%	High
	Q35	4.898	0.504	1.92%	0.58%	97.50%	High
	Q36	4.892	0.555	1.92%	0.77%	97.31%	High
	Q37	4.906	0.497	1.54%	0.58%	97.88%	High
	Overall	4.896	0.517	1.79%	0.91%	97.31%	High

1.4 Evaluation of the Study Model

The researcher employed a two-step method to analyze the study model, focusing on evaluating the measurement model and assessing the structural model to examine the research hypotheses. Before these steps, an assessment of data normality was conducted to ensure the suitability of the data for subsequent analysis. This involved examining skewness and kurtosis values, as well as performing Kolmogorov-Smirnov and Shapiro-Wilk tests, to identify any deviations from normality.

The measurement model evaluation included three primary stages: checking internal consistency reliability, assessing convergent validity, and evaluating discriminant validity. These steps ensured that the constructs were measured reliably and that the observed variables appropriately represented the latent constructs.

For the structural model evaluation, four key steps were undertaken: analyzing indicator multicollinearity, calculating the coefficient of determination (R^2), assessing predictive relevance (Q^2), and measuring effect size (f^2). These steps provided insights into the strength and predictive power of the hypothesized relationships within the study model. By following this systematic approach, the researcher ensured a comprehensive and rigorous evaluation of the study model.

1.4.1 Assessment of Data Normality

The study normality was assessed using skewness and kurtosis values. Where Skewness is a measure of the asymmetry of a distribution (Čisar, 2010). A distribution is asymmetrical when its left and right sides are not mirror images. Kurtosis measures the heaviness of a distribution's tails relative to a normal distribution (Čisar, 2010). Skewness values within ±2.0 and kurtosis values below 7.0 indicate normality (H.-Y. Kim, 2013). The Kolmogorov-Smirnov test results revealed a significance value of 0.000 ($P < 0.05$) across all variables, indicating significant deviations from normality, whereas The Kolmogorov–Smirnov (K–S) test is a non-parametric statistical method used to determine whether a sample comes from a specific distribution, such as the normal distribution (Serra & Nakamura, 2016).

Despite these findings, most variables exhibited skewness and kurtosis values within acceptable ranges. For instance, indicators such as RA-Q1 (skewness: 0.279, kurtosis: -1.299) and AI-A-Q13 (skewness: 0.289, kurtosis: -1.172) adhered to the normality thresholds. Figure 4.1 and Appendix (A) display these measures.

The Shapiro–Wilk test, introduced in 1965 by Shapiro and Wilk, is a statistical method used to assess whether a sample originates from a normally distributed population. It evaluates the null hypothesis that the data are normally distributed (De et al., 2020).The Shapiro-Wilk test further confirmed deviations from normality, as none of the variables met the threshold for normality ($P > 0.05$). For example, PAI-Q4 (Shapiro-Wilk statistic: 0.883, $P = 0.000$) and SL-Q37 (Shapiro-Wilk statistic: 0.876, $P = 0.000$) demonstrated significant deviations.

In summary, while most variables' skewness and kurtosis values fall within acceptable ranges, the Kolmogorov-Smirnov and Shapiro-Wilk tests indicate significant deviations from normality. These findings suggest that the data may not fully conform to the assumptions of normality, which should be considered when interpreting the results.

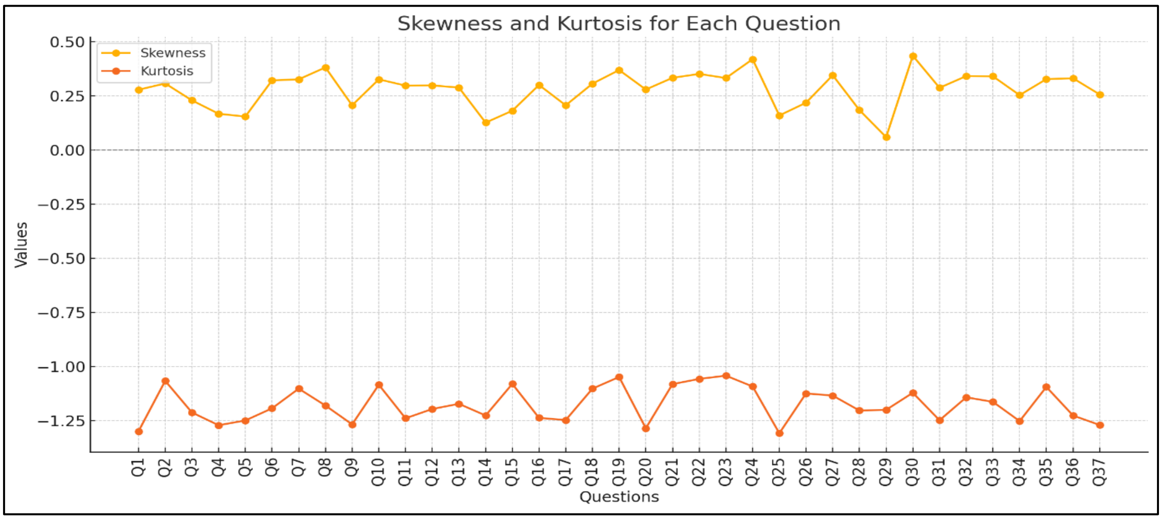

Figure (4.1): Frequency distribution of Skewness and Kurtosis

1.4.2 Internal Consistency Reliability

This stage assesses the consistency of results across items within a construct (Thompson, 2007). The reliability of the constructs was evaluated using Cronbach's Alpha (α) and Composite Reliability (CR) values, as shown in Table 4.6. Cronbach's alpha values of 0.70 or higher were considered acceptable, while values above 0.90 indicated excellent reliability Reference. Composite reliability values greater than 0.70 were deemed adequate, with 0.60 acceptable for exploratory research (J. Hair et al., 2010). The analysis reveals that most constructs exhibit moderate to strong internal consistency reliability.

For first-order constructs, AI Adoption (AI-A) achieved α = 0.669 and CR = 0.801, indicating moderate reliability. The perceived attributes of innovation (PAI) demonstrated strong reliability with α = 0.878 and CR = 0.900, while Relative Advantage (RA) achieved α = 0.823 and CR = 0.868, reflecting good reliability. Compatibility (CO) showed moderate reliability with α = 0.710 and CR = 0.821. ICT Readiness (ICT-R) displayed strong internal consistency, with α = 0.891 and CR = 0.908, and its sub-dimensions—ICT Infrastructure (ICT-I) (α = 0.679, CR = 0.805), ICT People and Human Resources (ICT-P) (α = 0.689, CR = 0.810), ICT Software (ICT-S) (α = 0.685, CR = 0.809), and ICT Hardware (ICT-H) (α = 0.595, CR = 0.787)—indicated moderate to strong reliability. Strategic Leadership (SL) also demonstrated good internal consistency, with α = 0.798 and CR = 0.852.

For second-order constructs, perceived attributes of innovation (PAI) achieved excellent reliability, with α = 0.874 and CR = 0.940. Similarly, ICT Readiness (ICT-R) displayed strong internal consistency with α = 0.871 and CR = 0.912.

These results indicate that most constructs exhibit strong internal consistency reliability, ensuring that the indicators within each construct are well-correlated and reliably measured. The findings affirm the robustness of the measurement model in capturing the dimensions of the study.

Table (4.6) Construct Reliability Analysis

Construct	α	CR
→ First Order		
AI-A	0.669	0.801
PAI	0.878	0.900
RA	0.823	0.868
CO	0.710	0.821
ICT-R	0.891	0.908
ICT-H	0.595	0.787
ICT-I	0.679	0.805
ICT-P	0.689	0.810
ICT-S	0.685	0.809
SL	0.798	0.852
→ Second Order		
PAI	0.874	0.940
ICT-R	0.871	0.912

1.4.3 Convergent Validity

Convergent validity is one of the topics related to construct validity. Convergent validity states that tests having the same or similar constructs should be highly correlated. According to J. F. Hair et al. (2014), convergent validity refers to "the extent to which a measure correlates positively with other measures of the same construct." To evaluate convergent validity in this study, the researcher applied two key tests: outer loading and average variance extracted (AVE).

1.4.4 Outer Loading

The outer loadings, as presented in Table 4.7, assess the strength of the relationship between constructs and their respective indicators. A loading above 0.60 is generally considered acceptable for convergent validity (J. F. Hair et al., 2014). The results highlight variations in indicator loadings across first- and second-order constructs.

For perceived attributes of innovation (PAI), the Relative Advantage (RA) indicators showed moderate loadings, with values ranging from 0.665 (Q1) to 0.739 (Q7). Similarly, the Compatibility (CO) indicators exhibited acceptable loadings, with values between 0.700 (Q8) and 0.780 (Q11). These results suggest moderate to strong associations between the indicators and their constructs. In the second order, RA (0.948) and CO (0.937) demonstrated excellent loadings, indicating strong relationships with the overall PAI construct.

For AI Adoption (AI-A), indicator loadings ranged from 0.670 (Q12) to 0.741 (Q15), with acceptable values across all items. However, some indicators, such as Q12 (0.670) and Q14 (0.681), showed slightly weaker associations, suggesting potential areas for improvement in their measurement reliability.

For ICT Readiness (ICT-R) and its sub-dimensions, loadings were generally strong. ICT Infrastructure (ICT-I) indicators ranged from 0.689 (Q16) to 0.742 (Q19), and ICT Hardware (ICT-H) showed loadings between 0.701 (Q20) and 0.768 (Q22). Similarly, ICT Software (ICT-S) demonstrated acceptable to strong loadings, with values from 0.605 (Q23) to 0.769 (Q26). ICT People and Human Resources (ICT-P) had loadings ranging from 0.655 (Q27) to 0.773 (Q30), with Q29 (0.655) slightly below the preferred range, indicating a weaker association. In the second order, ICT-I (0.852), ICT-H (0.832), ICT-S (0.844), and ICT-P (0.869) all demonstrated strong loadings, highlighting robust relationships with the overall ICT-R construct.

For Strategic Leadership (SL), loadings ranged from 0.612 (Q30) to 0.771 (Q37), indicating acceptable associations. However, Q36 (0.612) and Q35 (0.658) showed relatively weaker relationships with the construct, suggesting opportunities for refinement in their measurement.

In summary, the first-order constructs generally exhibit acceptable to strong loadings, with many indicators exceeding the 0.60 threshold for convergent validity. The second-order constructs, such as PAI and ICT-R, demonstrated strong loadings, indicating robust relationships between dimensions and their overarching constructs.

Table (4.7) Outer Loading of Indicators

Construct	Question	Outer Loading
→ First Order		
PAI		
RA	Q1	0.665
	Q2	0.672
	Q3	0.720
	Q4	0.739
	Q5	0.676
	Q6	0.723
	Q7	0.679
CO	Q8	0.733
	Q9	0.700
	Q10	0.712
	Q11	0.780
AI-A	Q12	0.670
	Q13	0.741
	Q14	0.681
	Q15	0.738
ICT-R		
ICT-I	Q16	0.689
	Q18	0.689
	Q19	0.732
ICT-H	Q20	0.768
	Q21	0.701
	Q22	0.760
ICT-S	Q23	0.736
	Q24	0.753
	Q25	0.769
	Q26	0.605
ICT-P	Q27	0.773
	Q28	0.671
	Q29	0.655
	Q30	0.770
SL	Q31	0.628
	Q32	0.683
	Q33	0.672
	Q34	0.771
	Q35	0.658
	Q36	0.612
	Q37	0.672
→ Second Order		

PAI		
	RA	0.948
	CO	0.937
ICT-R		
	ICT-I	0.852
	ICT-H	0.832
	ICT-S	0.844
	ICT-P	0.869

1.4.5 Average Variance Extracted (AVE)

The Average Variance Extracted (AVE) analysis provides insight into the convergent validity of the constructs by measuring the degree to which a construct explains the variance of its indicators. An AVE value of 0.50 or higher is generally considered acceptable, indicating that the construct explains at least 50% of the variance in its indicators (J. F. Hair et al., 2014).

For the first-order constructs as presented in Table 4.8, AI Adoption (AI-A) achieved an AVE of 0.502, meeting the threshold for convergent validity. Similarly, Compatibility (CO) (0.535), ICT Hardware (ICT-H) (0.553), ICT Infrastructure (ICT-I) (0.509), ICT People and Human Resources (ICT-P) (0.518), and ICT Software (ICT-S) (0.516) all exceeded the 0.50 threshold, demonstrating sufficient convergent validity. However, Perceived attributes of innovation (PAI) (0.450), Relative Advantage (RA) (0.486), Strategic Leadership (SL) (0.452), and ICT Readiness (ICT-R) (0.398) fell below the acceptable threshold, suggesting weaker convergent validity for these constructs.

For the second-order constructs, Perceived attributes of innovation (PAI) and ICT Readiness (ICT-R) achieved AVE values of 0.888 and 0.721, respectively, indicating strong convergent validity at the second-order level.

These results suggest that while the majority of constructs demonstrate adequate convergent validity, certain first-order constructs may require further refinement to strengthen their explanatory power.

Table (4.8) Average Variance Extracted (AVE) Analysis

Construct	AVE
→ First Order	
AI-A	0.502
PAI	0.450
RA	0.486
CO	0.535
ICT-R	0.398
ICT-H	0.553
ICT-I	0.509
ICT-P	0.518
ICT-S	0.516
SL	0.452
→ Second Order	
PAI	0.888
ICT-R	0.721

4.4.6 Discriminant Validity

4.4.6.1 Discriminant Validity 1st Order

This stage evaluates the extent to which a construct is truly distinct from other constructs (Zait et al., 2011). Discriminant validity was assessed using three methods: The Fornell-Larcker criterion, the Heterotrait-Monotrait (HTMT) ratio, and cross-loading analysis (Zait et al., 2011).

Fornell-Larcker Criterion: The Fornell-Larcker criterion evaluates discriminant validity by comparing the square root of the Average Variance Extracted (AVE) of each construct to its correlations with other constructs. For discriminant validity to be confirmed, the square root of the AVE must be greater than its correlation with any other construct (Fornell & Larcker, 1981). As shown in Table 4.9, most constructs meet this requirement, indicating good discriminant validity. For instance, AI-A has a square root of AVE of 0.708, higher than its correlations with other constructs. However, some constructs, such as ICT Readiness (ICT-R) and perceived attributes of innovation (PAI), exhibit high correlations, which may suggest potential overlap among constructs.

Heterotrait-Monotrait Ratio (HTMT): The HTMT ratio measures discriminant validity by examining the correlation between constructs. A threshold value of 0.85 is commonly used, although some studies allow for up to 0.90 construct (Fornell & Larcker, 1981). Table 4.10 indicates that most HTMT ratios exceed the threshold, such as PAI-CO (1.150) and ICT-R-ICT-H (1.160), suggesting significant correlations between constructs and potential challenges to discriminant validity.

Cross-Loading Analysis: Cross-loading analysis assesses how strongly indicators are associated with their intended constructs compared to other constructs. Ideally, an indicator should load higher on its respective construct than on others (Chin, 1998). The cross-loading results in Appendix (B) provide a detailed examination of how each indicator aligns with its respective construct compared to others. Indicators for Relative Advantage (RA), such as Q3 (0.720) and Q4 (0.739), demonstrate strong associations, whereas Q1 (0.665) and Q2 (0.672) show moderate loadings, indicating some room for improvement. For Compatibility (CO), indicators like Q8 (0.733) and Q11 (0.780) exhibit clear alignment with the construct, while Q9 (0.700) and Q10 (0.712) display slightly weaker but still acceptable loadings. AI Adoption (AI-A) indicators Q13 (0.741) and Q15 (0.738) show strong loadings, while Q12 (0.670) and Q14 (0.681) have acceptable but moderate associations.

For ICT Readiness (ICT-R), indicators such as Q17 (0.661) and Q19 (0.694) reflect strong relationships with the construct, but Q16 (0.597) demonstrates a weaker association. Similarly, indicators for ICT Hardware (ICT-H), such as Q20 (0.768) and Q22 (0.760), align well, but Q21 (0.701) shows a slightly lower loading. ICT Software (ICT-S) indicators Q25 (0.769) and Q27 (0.773) display strong associations, whereas Q26 (0.605) has a weaker loading, suggesting a less robust link with the construct. For ICT People (ICT-P), indicators

Q27 (0.773) and Q30 (0.770) demonstrate strong associations, but Q29 (0.655) has a moderate loading, indicating potential overlap with other constructs.

Strategic Leadership (SL) indicators, such as Q34 (0.771) and Q33 (0.672), exhibit strong alignment with the construct, while Q36 (0.612) and Q35 (0.658) show moderate associations, highlighting potential issues with discriminant validity. Overall, the cross-loading analysis supports the discriminant validity of most constructs, as indicators generally load highest on their respective dimensions. However, certain indicators, particularly in ICT-R, ICT-S, and SL, show weaker loadings and some overlaps, indicating areas that may require further refinement to enhance their distinctiveness and strengthen the overall measurement model.

In summary, while the Fornell-Larcker criterion supports discriminant validity for most constructs, the HTMT ratios indicate potential issues with high correlations between certain constructs, such as PAI and CO or ICT-R and ICT-H. The cross-loading analysis generally supports the distinctiveness of the constructs, though some overlap remains, particularly in highly correlated dimensions.

Table (4.9) Fornell-Larcker criterion (1st Order)

	AI-A	CO	PAI	ICT-R	ICT-H	ICT-I	ICT-P	ICT-S	RA	SL
AI -A	0.708									
CO	0.715	0.732								
PAI	0.803	0.907	0.671							
ICT-R	0.762	0.795	0.871	0.631						
ICT-H	0.619	0.679	0.744	0.846	0.743					
ICT-I	0.663	0.670	0.763	0.891	0.678	0.713				
ICT-P	0.678	0.729	0.766	0.892	0.688	0.744	0.720			
ICT-S	0.690	0.698	0.769	0.861	0.654	0.673	0.661	0.719		
RA	0.785	0.775	0.969	0.841	0.719	0.752	0.722	0.744	0.697	
SL	0.771	0.767	0.854	0.843	0.732	0.769	0.753	0.692	0.831	0.673

Table (4.10) Heterotrait-Monotrait ratio (1st Order)

	AI-A	CO	PAI	ICT-R	ICT-H	ICT-I	ICT-P	ICT-S	RA	SL
AI -A										
CO	1.039									
PAI	1.043	1.150								
ICT-R	0.980	0.998	0.984							
ICT-H	0.977	1.043	1.025	1.160						
ICT-I	0.976	0.957	0.985	1.142	1.057					
ICT-P	0.979	1.033	0.977	1.129	1.060	1.065				
ICT-S	1.013	0.996	0.988	1.101	1.016	0.983	0.949			
RA	1.051	1.012	1.139	0.982	1.020	1.005	0.951	0.988		
SL	1.035	1.012	1.016	0.999	1.060	1.044	1.004	0.930	1.023	

4.4.6.2 Discriminant Validity 2nd Order

The discriminant validity for second-order constructs was evaluated using the Fornell-Larcker criterion and the Heterotrait-Monotrait (HTMT) ratio.

Fornell-Larcker Criterion: The results in Table 4.11 show that the square root of the AVE for each construct (diagonal values) is higher than its correlations with other constructs (off-diagonal values). This confirms adequate discriminant validity for the second-order constructs. Notably, AI-A has a perfect diagonal value of 1.000, demonstrating no issues with overlap. The inter-construct correlation between PAI and ICT-R is relatively high at 0.846, but it remains below their respective AVE square roots. Similarly, SL and AI-A share a correlation of 0.773, which does not exceed the square root of their AVEs. Overall, the results affirm that second-order constructs are distinct from one another.

Heterotrait-Monotrait (HTMT) Ratio: As presented in Table 4.12, the HTMT ratios for most second-order constructs remain below the threshold of 0.85, further supporting discriminant validity. The highest HTMT value is observed between PAI and ICT-R (0.968), indicating a strong but acceptable relationship that does not indicate overlap. Other construct pairs, such as AI-A and ICT-R (0.790) and SL and ICT-R (0.851), remain within acceptable limits, confirming their distinction.

In summary, the second-order constructs demonstrate adequate discriminant validity, with the Fornell-Larcker criterion and HTMT ratios affirming that the constructs are distinct. While some correlations approach the threshold values, they remain within acceptable bounds, ensuring the constructs can be reliably interpreted as separate entities in the model.

Table (4.11) Fornell-Larcker criterion (2nd Order)

	AI-A	PAI	ICT-R	SL
AI -A	1.000			
PAI	0.798	0.942		
ICT-R	0.740	0.846	0.849	
SL	0.773	0.836	0.794	1.000

Table (4.12) Heterotrait-Monotrait ratio (2nd Order)

	AI-A	PAI	ICT-R	SL
AI -A				
PAI	0.852			
ICT-R	0.790	0.968		
SL	0.773	0.893	0.851	

4.5 Structural Model Assessment

Once the measurement model is validated, the structural model is assessed to examine the relationships (the hypothesized relationships) between constructs. The researcher conducted four tests to evaluate the structural model: the multicollinearity test, coefficient of determination (R^2), predictive relevance (Q^2), and effect size (f^2) tests.

4.5.1 Indicator multi-collinearity

Multicollinearity refers to high correlations among predictor variables, which can distort the estimation of path coefficients. Variance Inflation Factor (VIF) values are examined, with VIFs below 5 indicating acceptable levels of multicollinearity (Shrestha, 2020). The Variance Inflation Factor (VIF) was used to evaluate collinearity among indicators, as suggested by Fornell & Bookstein (1982). A VIF value greater than 5, or in stricter analyses above 3, indicates potential multi-collinearity, which can compromise the reliability of a construct. Table 4.13 summarizes the VIF statistics for each indicator across various constructs.

The results reveal that all VIF values are below the threshold of 5, confirming that there is no collinearity within the structural model. For perceived attributes of innovation (PAI), the VIF values for Relative Advantage (RA) indicators range from 1.416 (Q1) to 1.837 (Q4), while Compatibility (CO) indicators range from 1.273 (Q10) to 1.771 (Q11). These values indicate acceptable levels of collinearity.

For AI Adoption (AI-A), VIF values range between 1.224 (Q12) and 1.284 (Q15), demonstrating minimal collinearity. Similarly, ICT Readiness (ICT-R) sub-dimensions, including ICT Infrastructure (ICT-I) and ICT Hardware (ICT-H), exhibit VIF values ranging from 1.215 (Q16) to 1.511 (Q22), indicating strong reliability. ICT Software (ICT-S) indicators range from 1.164 (Q26) to 1.564 (Q23), while ICT People (ICT-P) indicators have VIF values between 1.272 (Q29) and 2.000 (Q30).

For Strategic Leadership (SL), the VIF values range from 1.363 (Q31) to 1.683 (Q34), remaining well below the threshold, confirming the absence of collinearity.

Overall, the VIF statistics across all indicators and constructs demonstrate that collinearity is not a concern in the model. The absence of high collinearity ensures the reliability and stability of the constructs in the structural model, enabling accurate and robust data interpretation.

Table (4.13) Result of Collinearity Statistics (VIF) for Indicators

Construct	Question	VIF
PAI		
RA	Q1	1.416
	Q2	1.481
	Q3	1.615
	Q4	1.837
	Q5	1.463
	Q6	1.599

	Q7	1.640
CO	Q8	1.385
	Q9	1.280
	Q10	1.273
	Q11	1.771
AI-A	Q12	1.224
	Q13	1.281
	Q14	1.241
	Q15	1.284
ICT-R		
ICT-I	Q16	1.250
	Q17	1.328
	Q18	1.274
	Q19	1.270
ICT-H	Q20	1.215
	Q21	1.511
	Q22	1.435
ICT-S	Q23	1.564
	Q24	1.540
	Q25	1.376
	Q26	1.164
ICT-P	Q27	1.390
	Q28	1.407
	Q29	1.272
	Q30	2.000
SL	Q31	1.363
	Q32	1.526
	Q33	1.445
	Q34	1.683
	Q35	1.394
	Q36	1.415
	Q37	1.412

4.5.2 Coefficient of Determination (R^2)

The coefficient of determination (R^2) measures the proportion of variance in an endogenous construct explained by all exogenous constructs, indicating the model's predictive accuracy. R^2 values range from 0 to 1, with higher values reflecting stronger explanatory power. According to Cohen (2013), R^2 values of 0.02, 0.15, and 0.35 are interpreted as weak, moderate, and strong, respectively.

The results in Table 4.14 reveal that AI Adoption (AI-A) achieves an R^2 value of 0.679, indicating high explanatory power. Both perceived attributes of innovation (PAI) and ICT Readiness (ICT-R) demonstrate perfect explanatory power with R^2 values of 1.000, reflecting exceptional predictive accuracy for these constructs.

Overall, the findings confirm the structural model's strong predictive capacity for these constructs, supporting its robustness and reliability in explaining the variance in AI-A, PAI, and ICT-R. These results validate the model's ability to capture the relationships between exogenous and endogenous constructs effectively.

Table (4.14) Results of R^2

Construct	R^2	Degree
AI-A	0.679	High
PAI	1.000	High
ICT-R	1.000	High

4.5.3 Predictive Relevance (Q^2)

Predictive Relevance Q^2 assesses the model's predictive accuracy through techniques like blindfolding. A Q^2 value greater than zero indicates that the model has predictive relevance for a particular endogenous construct (Yovi et al., 2023).

The results in Table 4.15 confirm that all Q^2 values are significantly greater than zero, demonstrating strong predictive relevance for the exogenous constructs. AI Adoption (AI-A) achieves a Q^2 value of 0.68, reflecting substantial predictive relevance. Both perceived attributes of innovation (PAI) and ICT Readiness (ICT-R) attain perfect Q^2 values of 1.00, indicating exceptional predictive capability.

These findings highlight the model's robust ability to predict indicator data points, affirming the predictive relevance of the exogenous constructs for their respective endogenous constructs. This result validates the structural model's strength and reliability in forecasting the relationships among the constructs.

Table (4.15) Results of Q^2

Construct	Q^2
AI-A	0.68
PAI	1
ICT-R	1

4.5.4 Effect Size (f^2) tests

Effect size (f^2) assesses the impact of individual exogenous constructs on endogenous constructs by measuring the unique variance explained by the focal variable when removed from the structural model (Chin, 1998). Effect sizes are classified as small (0.02), medium (0.15), and large (0.35) (Cohen, 1992).

The results in Table 4.16 demonstrate consistently high f^2 values across the model, indicating significant contributions of exogenous constructs to their respective endogenous constructs. For perceived attributes of innovation (PAI), Relative Advantage (RA) shows an exceptionally high effect size (3511.135) on PAI, followed by Compatibility (CO) with an f^2 value of 1188.631. These results highlight the dominant influence of RA and CO on PAI, underscoring their importance in driving innovation diffusion.

For ICT Readiness (ICT-R), the effect sizes of its components are equally substantial. ICT Hardware (ICT-H) exhibits an f^2 value of 678.498, while ICT Infrastructure (ICT-I) has a higher effect size of 971.860. Additionally, ICT Processes (ICT-P) (1023.892) and ICT Support (ICT-S) (1222.047) contribute significantly to ICT-R, emphasizing the critical roles of these components in enhancing overall ICT readiness.

These findings indicate that the structural model demonstrates strong explanatory power, with consistently high effect sizes reinforcing the substantial influence of key exogenous constructs on their respective endogenous constructs. This underscores the robustness of the model in capturing the relationships and contributions of these constructs.

Table (4.16) Results of f^2

Construct	Indicators	f^2	Degree
PAI	RA → PAI	3511.135	High
	CO → PAI	1188.631	High
ICT-R	ICT-H → ICT-R	678.498	High
	ICT-I → ICT-R	971.860	High
	ICT-P → ICT-R	1023.892	High
	ICT-S → ICT-R	1222.047	High

4.6 Research Hypotheses Testing

The final phase of structural model evaluation entails analyzing the hypothesized relationships through the path coefficient test. By the recommendations of Jr et al. (2017), bootstrapping techniques utilizing 5,000 subsamples were applied to assess the proposed hypotheses.

The results of the study hypotheses are illustrated in Figure 4.2. In the path analysis, the values displayed within the inner model represent the outcomes of the hypothesized relationships.

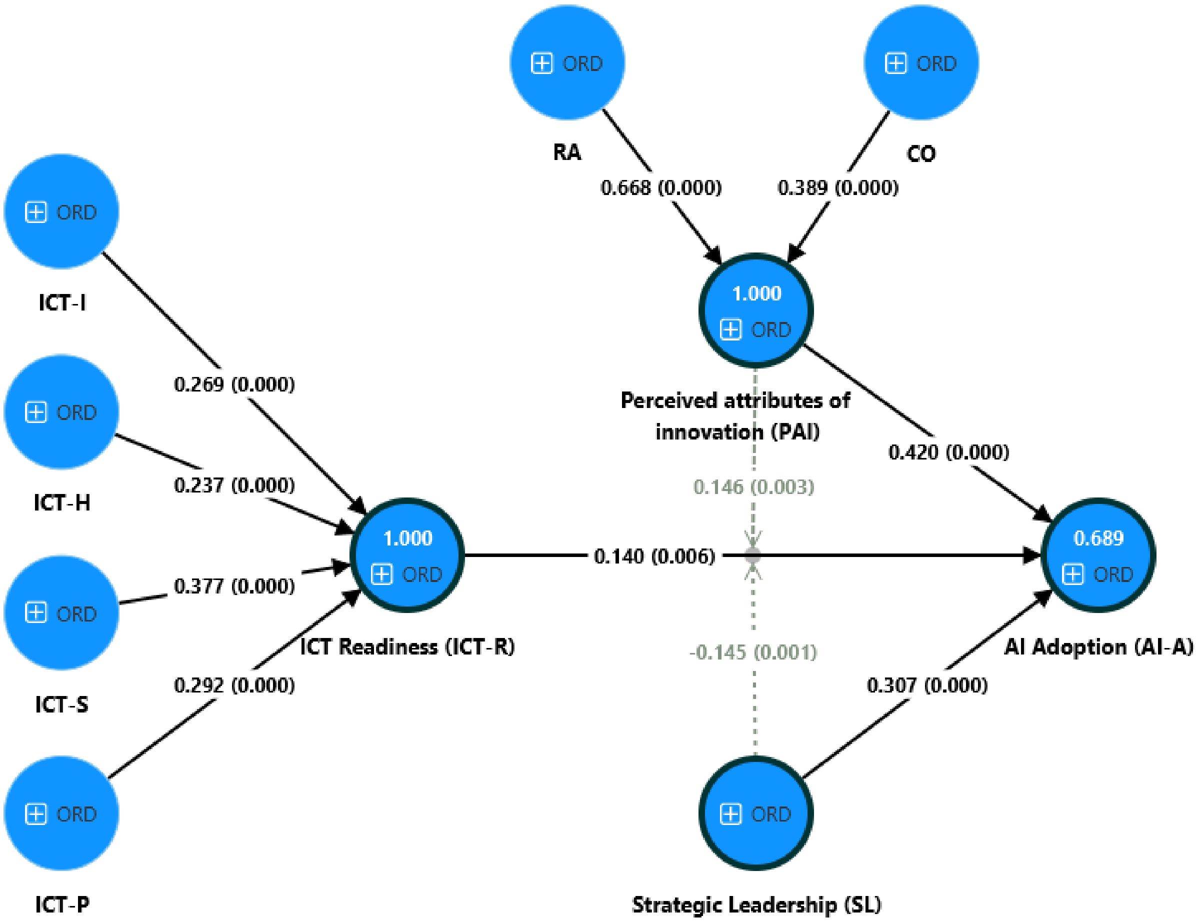

Figure (4.2) Results of Path Analysis

*Values in the inner model represent the (p-value); the outer model represents β-value.

4.6.1 Results of the Hypothesis

4.6.2 ICT Readiness and AI Adoption

The hypothesis examines the relationship between ICT Readiness and AI Adoption. “H1: ICT readiness factors are positively related to AI adoption.” As shown in Table 4.17, there is a significant positive relationship between ICT Readiness and AI Adoption, with a path coefficient of β = 0.140, t = 2.544, and a p-value of 0.006. Since the p-value is below the significance threshold of 0.05, H1 is supported.

These findings indicate that an increase of one unit in ICT Readiness leads to a 0.140-unit increase in AI Adoption. This highlights the critical role of ICT Readiness in facilitating

AI adoption within the structural model, affirming the hypothesis and emphasizing the importance of ICT components in driving advancements in AI implementation.

Table (4.17) Results of the First Hypothesis

Hypothesis	Direction	β coefficient	Std.	t values	p values	Result
H1	ICT-R → AI-A	0.140	0.055	2.544	0.006	Supported

*Note. **P<0.05*

4.6.3 Sub-Hypotheses: ICT Readiness Factors & AI Adoption

The sub-hypotheses examine the relationship between specific ICT Readiness factors and AI Adoption. Each sub-hypothesis focuses on a distinct aspect of ICT Readiness: infrastructure, hardware, information systems and software, and people and human resources.

- **H1$_a$**: The ICT infrastructure factor is positively related to AI adoption. The results in Table 4.18 show a significant positive relationship between ICT Infrastructure (ICT-I) and AI Adoption, with a path coefficient of $\beta = 0.038$, $t = 2.543$, and a p-value of 0.006. As the p-value is below 0.05, H1a is supported, indicating that ICT Infrastructure positively influences AI Adoption.
- **H1$_b$:** The ICT hardware factor is positively related to AI adoption. For ICT Hardware (ICT-H), the path coefficient is $\beta = 0.033$, with $t = 2.528$ and a p-value of 0.006. These results support H1b, confirming that ICT Hardware contributes positively to AI Adoption.
- **H1$_c$:** The ICT information system and software is positively related to AI adoption. The relationship between ICT Information Systems and Software (ICT-S) and AI Adoption is also significant, with a path coefficient of $\beta = 0.053$, $t = 2.529$, and a p-value of 0.006. H1c is therefore supported, highlighting the role of software and information systems in enhancing AI Adoption.

- **$H1_d$:** ICT people and human resources factors are positively related to AI adoption. ICT People and Human Resources (ICT-P) show a significant positive relationship with AI Adoption, with a path coefficient of β = 0.041, t = 2.526, and a p-value of 0.006. This supports H1d, emphasizing the critical role of human resources in AI Adoption.

The results demonstrate that all ICT Readiness factors—Infrastructure, Hardware, Information Systems and Software, and People and Human Resources—positively and significantly influence AI Adoption. These findings affirm the importance of comprehensive ICT readiness in driving successful AI implementation, supporting the sub-hypotheses H1a, H1b, H1c, and H1d.

Table (4.18) Results of the First Sub-Hypothesis

Hypothesis	Direction	β coefficient	Std.	t values	p values	Result
$H1_a$	ICT-I → AI-A	0.038	0.015	2.543	0.006	Supported
$H1_b$	ICT-H → AI-A	0.033	0.013	2.528	0.006	Supported
$H1_c$	ICT-S → AI-A	0.053	0.021	2.529	0.006	Supported
$H1_d$	ICT-P → AI-A	0.041	0.016	2.526	0.006	Supported

*Note. **P<0.05*

4.6.4 Strategic Leadership as a Moderator

The second hypothesis investigates whether Strategic Leadership (SL) positively moderates the relationship between ICT Readiness (ICT-R) factors and AI Adoption. **H2**: Strategic Leadership positively moderates the relationship between ICT readiness factors and AI adoption.

The results, as shown in Table 4.19, indicate a significant moderation effect, with a path coefficient of β = -0.145, t = 3.076, and a p-value of 0.001. Since the p-value is below the 0.05 threshold, H2 is supported. However, the negative coefficient (β = -0.145) suggests that the moderating effect of Strategic Leadership on the relationship between ICT Readiness and AI

Adoption weakens the strength of this relationship rather than enhancing it. In other words, Strategic Leadership appears to reduce the impact of ICT readiness factors on AI adoption instead of amplifying it as initially hypothesized. This result indicates that the role of leadership in moderating the relationship between ICT readiness and AI adoption may not always be straightforwardly positive. Instead, it might introduce complexities or constraints that diminish the effectiveness of ICT readiness in adopting AI. Potential explanations for this negative path coefficient will be interpreted and further discussed in Chapter Five, including an exploration of similar findings in related literature to provide deeper insights into this phenomenon.

Table (4.19) Results of the Second Hypothesis

Hypothesis	**Direction**	β **coefficient**	**Std.**	t **values**	p **values**	**Result**
H2	ICT-R → SL → AI-A	-0.145	0.047	3.076	0.001	Supported

*Note. **P<0.05*

4.6.5 Sub-Hypotheses: Strategic Leadership as a Moderator

This section examines the moderating role of Strategic Leadership (SL) in the relationship between specific ICT Readiness factors and AI Adoption. Each sub-hypothesis focuses on a different component of ICT Readiness: Infrastructure, Hardware, Information Systems and Software, and People and Human Resources.

- **H2$_a$**: Strategic Leadership positively moderates the relationship between the ICT infrastructure factor and AI adoption. The results in Table 4.20 show a significant moderating effect of Strategic Leadership on the relationship between ICT Infrastructure (ICT-I) and AI Adoption, with a path coefficient of β = -0.129, t = 2.427, and a p-value of 0.008. While the hypothesis is supported, the negative coefficient indicates that Strategic Leadership weakens the direct relationship between ICT-I and AI Adoption.

- **H2$_b$**: Strategic Leadership positively moderates the relationship between the ICT hardware factor and AI adoption. For ICT Hardware (ICT-H), the moderating effect of Strategic Leadership is also significant, with β = -0.072, t = 1.938, and a p-value of 0.026. As with H2a, the negative coefficient suggests that Strategic Leadership reduces the strength of this relationship.
- **H2$_c$**: Strategic Leadership positively moderates the relationship between the ICT information system and software factor and AI adoption. The results for ICT Information Systems and Software (ICT-S) show a positive and significant moderating effect, with β = 0.114, t = 2.991, and a p-value of 0.001. This indicates that Strategic Leadership enhances the relationship between ICT-S and AI Adoption.
- **H2$_d$**: Strategic Leadership positively moderates the relationship between the people and human resources factor and AI adoption. For ICT People and Human Resources (ICT-P), Strategic Leadership also demonstrates a positive and significant moderating effect, with β = 0.129, t = 2.709, and a p-value of 0.003. This confirms that Strategic Leadership strengthens the relationship between ICT-P and AI Adoption.

The results show mixed moderating effects of Strategic Leadership across the ICT Readiness factors. While Strategic Leadership positively enhances the relationships for ICT Information Systems and Software (H2c) and ICT People and Human Resources (H2d), it weakens the relationships between ICT Infrastructure (H2a) and ICT Hardware (H2b). These findings suggest that the impact of Strategic Leadership as a moderator varies depending on the specific ICT Readiness factor.

Table (4.20) Results of the Second Sub-Hypothesis

Hypothesis	Direction	β coefficient	Std.	t values	p values	Result
H2$_a$	ICT-I → SL → AI-A	-0.129	0.053	2.427	0.008	Supported
H2$_b$	ICT-H→ SL → AI-A	-0.072	0.037	1.938	0.026	Supported

H2$_c$	ICT-S → SL → AI-A	0.114	0.038	2.991	0.001	Supported
H2$_d$	ICT-P→ SL → AI-A	0.129	0.047	2.709	0.003	Supported

*Note. **P<0.05*

4.6.6 Perceived attributes of innovation (PAI) as a Moderator

This hypothesis examines whether the perceived attributes of innovation, specifically Relative Advantage and Compatibility, moderate the relationship between ICT Readiness factors and AI Adoption. **H3**: Perceived attributes of innovation (Relative Advantage/Compatibility) moderate the relationship between ICT readiness factors and AI adoption.

The results, as presented in Table 4.21, indicate a significant moderating effect of perceived attributes of innovation on the relationship between ICT Readiness (ICT-R) and AI Adoption, with a path coefficient of β = 0.146, t = 2.784, and a p-value of 0.003. Since the p-value is below the 0.05 significance threshold, H3 is supported.

The positive coefficient indicates that perceived attributes of innovation enhance the impact of ICT Readiness on AI Adoption. This suggests that when organizations perceive ICT systems as offering clear advantages and being compatible with existing practices, the relationship between ICT readiness and AI adoption becomes stronger.

Table (4.21) Results of the Third Hypothesis

Hypothesis	Direction	β coefficient	Std.	t values	p values	Result
H3	ICT-R → PAI→ AI-A	0.146	0.053	2.784	0.003	Supported

*Note. **P<0.05*

4.6.7 Sub-Hypotheses: perceived attributes of innovation as Moderators

This section explores perceived attributes of innovation, specifically Relative Advantage (RA) and Compatibility (CO), and moderates the relationships between ICT

Readiness factors (Infrastructure, Hardware, Information Systems, and People/Human Resources) and AI Adoption as presented in Table 4.22.

Relative Advantage as a Moderator:

- **$H3_a$**: Relative Advantage moderates the relationship between ICT Infrastructure (ICT-I) and AI Adoption. The results show a significant positive moderating effect, with β = 0.038, t = 2.543, and p = 0.006, supporting H3a.
- **$H3_b$**: Relative Advantage moderates the relationship between ICT Hardware (ICT-H) and AI Adoption. The findings indicate a significant positive effect, with β = 0.033, t = 2.528, and p = 0.006, supporting H3b.
- **$H3_c$**: Relative Advantage moderates the relationship between ICT Information Systems (ICT-S) and AI Adoption. The results show β = 0.053, t = 2.529, and p = 0.006, supporting H3c.
- **$H3_d$**: Relative Advantage moderates the relationship between ICT People and Human Resources (ICT-P) and AI Adoption. The analysis reveals a significant positive effect, with β = 0.041, t = 2.526, and p = 0.006, supporting H3d.

Compatibility as a Moderator:

- **$H3_e$**: Compatibility moderates the relationship between ICT Infrastructure (ICT-I) and AI Adoption. The results reveal a significant positive moderating effect, with β = 0.269, t = 27.121, and p = 0.000, supporting H3e.
- **$H3_f$**: Compatibility moderates the relationship between ICT Hardware (ICT-H) and AI Adoption. The findings indicate a strong positive effect, with β = 0.237, t = 22.269, and p = 0.000, supporting H3f.
- **$H3_g$**: Compatibility moderates the relationship between ICT Information Systems (ICT-S) and AI Adoption. The results show β = 0.377, t = 31.009, and p = 0.000, supporting H3g.

- **$H3_h$**: Compatibility moderates the relationship between ICT People and Human Resources (ICT-P) and AI Adoption. The analysis reveals a significant positive effect, with $\beta = 0.292$, $t = 29.124$, and p = 0.000, supporting H3h.

The results confirm that both Relative Advantage and Compatibility significantly enhance the relationships between ICT Readiness factors and AI Adoption. Relative Advantage demonstrates consistent positive moderation across all ICT factors (H3a–H3d), while Compatibility shows stronger moderating effects (H3e–H3h). These findings highlight the critical role of perceived innovation attributes in strengthening the impact of ICT readiness on AI adoption.

Table (4.22) Results of the Third Sub-Hypothesis

Hypothesis	Direction	β coefficient	Std.	t values	p values	Result
$H3_a$	ICT-I → RA→ AI-A	0.038	0.015	2.543	0.006	Supported
$H3_b$	ICT-H → RA→ AI-A	0.033	0.013	2.528	0.006	Supported
$H3_c$	ICT-S → RA→ AI-A	0.053	0.021	2.529	0.006	Supported
$H3_d$	ICT-P → RA→ AI-A	0.041	0.016	2.526	0.006	Supported
$H3_e$	ICT-I → CO→ AI-A	0.269	0.010	27.121	0.000	Supported
$H3_f$	ICT-H → CO→ AI-A	0.237	0.011	22.269	0.000	Supported
$H3_g$	ICT-S → CO→ AI-A	0.377	0.012	31.009	0.000	Supported
$H3_h$	ICT-P → CO→ AI-A	0.292	0.010	29.124	0.000	Supported

*Note. **P<0.05*

4.6.8 Constructs Direct Effect

This section presents the direct relationships among constructs in the structural model. The results, as outlined in Table 4.23, demonstrate significant direct effects, with all tested hypotheses supported (p < 0.05).

Direct Effects on AI Adoption (AI-A):

- Perceived attributes of innovation (PAI): A strong positive effect was observed (β = 0.424, t = 7.848, p = 0.000), indicating that PAI significantly influences AI Adoption.
- Relative Advantage (RA): The direct effect was significant, with β = 0.283, t = 7.757, p = 0.000, confirming its positive impact on AI Adoption.
- Compatibility (CO): A positive effect was found (β = 0.164, t = 7.686, p = 0.000), suggesting CO plays a role in driving AI Adoption.
- Strategic Leadership (SL): The results show a strong positive effect of SL on AI Adoption (β = 0.305, t = 6.068, p = 0.000).

Direct Effects on perceived attributes of innovation (PAI):

- ICT Readiness (ICT-R): The results indicate a significant positive relationship (β = 0.379, t = 7.226, p = 0.000).
- ICT Infrastructure (ICT-I): A moderate positive effect was observed (β = 0.102, t = 7.023, p = 0.000).
- ICT Hardware (ICT-H): A smaller but significant positive effect was found (β = 0.092, t = 6.806, p = 0.000).
- ICT Software (ICT-S): A stronger effect was observed (β = 0.142, t = 7.103, p = 0.000).
- ICT People (ICT-P): The results show a significant positive impact (β = 0.111, t = 6.927, p = 0.000).

Direct Effects on Strategic Leadership (SL):

- ICT Readiness (ICT-R): The strongest effect in the model was observed here (β = 0.794, t = 56.631, p = 0.000), confirming a dominant influence of ICT Readiness on SL.
- ICT Infrastructure (ICT-I): A significant positive effect was found (β = 0.214, t = 24.383, p = 0.000).

- ICT Hardware (ICT-H): A moderate positive impact was observed (β = 0.192, t = 20.742, p = 0.000).
- ICT Software (ICT-S): A strong positive effect was identified (β = 0.297, t = 27.045, p = 0.000).
- ICT People (ICT-P): The results also show a significant positive impact (β = 0.232, t = 26.731, p = 0.000).

All direct effects tested in the structural model were significant, with β coefficients ranging from moderate to strong. These findings underscore the importance of ICT Readiness, its components (Infrastructure, Hardware, Software, and People), and Strategic Leadership in influencing AI Adoption and perceived attributes of innovation. The results validate the hypothesized direct relationships and emphasize the interconnectedness of these factors in driving organizational innovation and technology adoption.

Table (4.23) Results of the Direct Effect

Direction	**β coefficient**	**Std.**	**t values**	**p values**	**Result**
PAI→ AI-A	0.424	0.054	7.848	0.000	Supported
RA → AI-A	0.283	0.036	7.757	0.000	Supported
CO → AI-A	0.164	0.021	7.686	0.000	Supported
SL → AI-A	0.305	0.05	6.068	0.000	Supported
ICT-R → PAI	0.379	0.053	7.226	0.000	Supported
ICT-I → PAI	0.102	0.015	7.023	0.000	Supported
ICT-H → PAI	0.092	0.013	6.806	0.000	Supported
ICT-S → PAI	0.142	0.02	7.103	0.000	Supported
ICT-P → PAI	0.111	0.016	6.927	0.000	Supported
ICT-R → SL	0.794	0.014	56.631	0.000	Supported
ICT-I → SL	0.214	0.009	24.383	0.000	Supported
ICT-H → SL	0.192	0.009	20.742	0.000	Supported

ICT-S → SL	0.297	0.011	27.045	0.000	Supported
ICT-P → SL	0.232	0.009	26.731	0.000	Supported

*Note. **P<0.05*

4.7 Chapter Four Summary

This chapter provides a comprehensive analysis of the study's findings, beginning with the demographic characteristics of respondents, followed by descriptive statistics, assessment of data normality, and evaluation of measurement model reliability and validity. A total of 520 participants were surveyed, with demographic data highlighting diversity in gender, age, job roles, managerial experience, education, and sector representation. Key descriptive statistics demonstrated high levels of agreement across constructs such as ICT Readiness (ICT-R), AI Adoption (AI-A), Perceived Attributes of Innovation (PAI), and Strategic Leadership (SL) underscoring their importance in the organizational context. Hypothesis testing revealed significant positive relationships among constructs, with all primary and sub-hypotheses supported. ICT Readiness and its components (Infrastructure, Hardware, Software, and People) were found to positively influence AI Adoption, moderated by Strategic Leadership and Perceived Attributes of Innovation (Relative Advantage and Compatibility). The results emphasize the critical role of these factors in driving innovation and technology adoption in organizational contexts.

Chapter Five

Discussion of Findings, Conclusions, and Recommendations

5.1 Introduction

This chapter provides a detailed discussion of the study's findings, situating them within the context of Palestine and aligning them with the research objectives and assumptions. It examines the implications of these findings for adopting and implementing AI, highlighting the role of leadership strategies and the perceived characteristics of innovation in this process. By connecting the results with theoretical frameworks, as well as with prior studies, the chapter contributes to a deeper understanding of AI integration in politically complex and developing countries. Additionally, it identifies practical implications for policymakers, organizational leaders, and practitioners, offering strategies to overcome barriers and harness AI for development within the unique Palestinian context.

5.2 ICT Readiness and AI Adoption

The results of the first hypothesis and sub-hypotheses "**H1**: ICT readiness factors are positively related to AI adoption" are positively related, with a significant path coefficient of β = 0.14, a t-value of 2.544, and a p-value 0.006. This evidence substantiates hypothesis H1, namely the fact that ICT readiness acts as a catalyst for the adoption of AI technologies by organizations. This has proven like the Resource-Based View (RBV) theory which emphasizes the need to leverage internal resources such as infrastructure, technology, and human capital to attain a competitive advantage (Barney, 1991). The findings suggested that AI adoption would increase with 0.14 units for each unit increase made to ICT-R, hence proving the key role, that ICT components play in assisting in penetrating and extending AI advancement implementation. This is, as hypothesized, in connection with the Technology-Organization-

Environment (TOE) framework, which posits conditions under which organization readiness becomes a major determinant of technology adoption (Tornatzky & Klein, 1982). In particular, a positive relationship between ICT-R and AI application adoption, and a strong infrastructure, hardware, software support systems, and skilled personnel would be needed in AI initiatives.

Additionally, the result aligns with Uren & Edwards (2023) study, which emphasizes that technology readiness, encompassing aspects like infrastructure and data management, is essential for the successful implementation of AI systems. Similarly, Issa et al. (2022) research highlights that firms with higher levels of technological readiness are more inclined to adopt AI solutions as they possess the necessary foundational capabilities to support such advanced technologies.

Notably, all these findings hold relevance for MSMEs in Palestine with findings that are corroborated by research done by Abu Abu Mansour (2022), which states that ICT-R is the leading factor speeding digitization across Palestinian businesses. These findings imply that incorporating artificial intelligence into Palestinian MSMEs would demand comprehensive ICT competence, which encompasses hardware, software, infrastructure, and human resources. Solomon Nsor-Anabiah et al. (2019), consider this in line with more mainstream literature on technology adoption in developing nations, which requires extensive technical preparedness to spur innovation and competitiveness in low-resource settings. Mashvisor, an AI-powered real estate analytics platform, demonstrates how Palestinian startups can harness advanced technologies to provide valuable insights for global markets (Mashvisor, 2024). The company's use of AI and machine learning algorithms to analyze potential short-term rental investments showcases the potential for Palestinian MSMEs to compete in high-tech sectors (Mashvisor, 2024).

A thorough investigation into the sub-hypotheses, evidentially concludes that some ICT-R factors tend to establish a positive effect on AI adoption. Altogether, the factors are singular contributors to the adoption process showing that ICT-R is such a multidimensional construct. ICT Infrastructure (ICT-I) and AI Adoption (**H1a**): The significant positive relationship between ICT-I and AI adoption (β = 0.038, t = 2.543, p = 0.006), which emphasizes the fact that, without infrastructure, adoption of AI technologies is virtually impossible. It guarantees reliable connectivity, data flow, and system integration which are essential for the deployment of AI. This goes with Porter's value chain model, which identifies how the roles of technologies and infrastructures form a base for competitive edge (Mckinsey & Company, 2021). This is exemplified by companies like Amazon, which leveraged its robust cloud infrastructure Amazon Web Services (AWS) to develop and deploy AI solutions across its operations (Baskar Sridharan & Peter Hallinan, 2024). ICT Hardware and AI Adoption (**H1b**): The study also found a significant relationship between ICT-H and AI adoption (β = 0.033, t = 2.528, p = 0.006), revealing a very significant one. This infers that high-quality and reliable hardware systems are essential in the implementation of AI technologies. Such evidence affirms what is contained in development literature by a resource-based view (RBV) of firms, as espoused by scholars like Barney, whose view was that, in firms, tangible resources drive technological innovations (Barney, 1991). As was shown by Apple's custom-made chips for working on AI processes in its devices. Such is represented by the announcement by Apple of the M3 family of chips as a large upgrade from the previous hardware capability on tasks designed specifically for AI and machine learning (Apple, 2023). ICT Information Systems and Software and AI Adoption (**H1c**): The relationship between ICT software and AI adoption (β = 0.053, t = 2.529, p = 0.006) underscores the role of integrated information systems and software in enabling AI functionality. Well-designed software solutions streamline data processing, analysis, and decision-making, facilitating seamless AI implementation. These findings align with the dynamic capabilities theory proposed by Teece et al. (1997), highlighting the importance of continuously reconfiguring technological resources also focuses on an organization's ability to integrate, build, and reconfigure internal competencies to address rapidly changing environments. Tesla's ability to update its vehicles' software for enhanced AI-driven features rapidly exemplifies this concept. This is evident in Tesla's recent holiday update, which included significant improvements to their Full Self-Driving (FSD) Supervised system (Zachary Visconti, 2024). (**H1d**): The significant positive relationship between ICT human resources and AI adoption (β = 0.041, t = 2.526, p = 0.006) highlights the importance of skilled personnel in the successful implementation of AI technologies. This finding aligns with the Knowledge-Based View (KBV) of the firm, as discussed by Grant (1996), emphasizing the critical role of human capital in technological innovation and competitive advantage (Halawi et al., 2005). Porter's Value Chain Analysis which considers human resource capital as an important supporting function that elevates organizational worth, is further endorsed (Mckinsey & Company, 2021). Brey (2023) proves the importance of complementary resources including ICT and managerial expertise, digital capabilities, and digital infrastructure, which are crucial for the adoption and diffusion of AI.

5.3 Strategic Leadership, ICT Readiness, and AI Adoption

The findings of this study offer support for the second hypothesis (**H2**), indicating that Strategic Leadership (SL) influences the relationship between ICT Readiness (ICT-R) factors and AI Adoption (AI-A). However, the results are mixed: Infrastructure (ICT-I) and ICT Hardware (ICT-H) have a negative impact, while ICT Systems and Software (ICT-S), and ICT People and Human Resources (ICT-P) have a positive effect.

The mixed results across ICT factors reflect the complexity of Strategic Leadership's role in AI adoption, emphasizing the need for context-specific approaches. The Resource-Based View (RBV) further reinforces this argument emphasizing that beyond resources, such as ICT infrastructure, they are not sufficient alone without strong leadership to manage them (Halawi et al., 2005).

The Contingency Theory of Leadership confirms that "leadership is context-dependent," and it emphasizes the importance of flexibility and adaptability in decision-making (Aumüller & Meyer, 2024; Nassou & Bennani, 2024). Moreover, Mintzberg's idea of strategy creation as a continuous, emergent process implies how important it is for leaders to handle turning obstacles (Mintzberg, 1994). However, in such a situation, it might indicate more leadership engagement in affecting the direct influence of ICT resources upon the adoption of AI. This coincidental finding suggests that strategic leadership may provide a barrier or hurdle reducing the effectiveness of ICT readiness in artificial intelligence implementation.

The findings reveal unexpected complexities. The moderation effect is significant (β = -0.145, t = 3.076, p = 0.001but the negative coefficient indicates that Strategic Leadership weakens, rather than enhances, the direct relationship between ICT Readiness and AI Adoption. This dynamic is particularly evident in ICT-I (β = -0.129, t = 2.427, p = 0.008) and ICT-H (β = -0.072, t = 1.938, p = 0.026). These results suggest that Strategic Leadership, while critical, may inadvertently create bottlenecks in leveraging ICT resources for AI adoption. This is consistent with literature indicating that excessively rigid or centralized leadership can inhibit flexibility and innovation (House & Aditya, 1997). Over-controlling decision-making processes or misaligning resources with technological objectives often hampers the full potential of ICT readiness (Valença et al., 2018). Bass (1990) and Mintzberg (1994) further emphasize that leadership focusing excessively on short-term goals can impair long-term strategic initiatives, reducing organizational flexibility and adaptability.

Managers, particularly those in resource-constrained systems, tend to focus on the effective use of current resources instead of expansion, and this forms the basis for Resource Constraints Theory which explains the negative moderating effect of hardware and infrastructure investments as experienced in Palestinian MSMEs (Galli, 2019; XU et al., 2023). Evidence from systematic assessments of the application of digital technology in SMEs within developing nations, which is based on regulatory impediments together with limited resources, corroborates this (Dimoso & Utonga, 2024). The level of challenges regarding strategic leadership is worsened in resource-poor environments such as Palestine, where politics and economics pose further barriers. Environmental challenges like fragmented communication, political unpredictability, and inadequate ICT resources further compound the difficulty in the adoption of AI (Alfoqahaa, 2015; World Bank, 2018). Most often, micro, small, and medium-sized enterprises (MSMEs) in Palestine experience mismatched resources, combined with very controlling leadership styles which further suffocate creativity and flexibility. In such cases, leaders are always forced to give precedence to immediate operational matters rather than spending on long-term technology costs (Musleh, 2022; Pires & Stanton, 2005).

The Resource-Based View (RBV) postulates that, without effective top management to strategically optimize resource use, mere ICT infrastructure will be inadequate (Al-Alawi et al., 2023; Andreu, 1993; Dunford et al., 2001; Gerhart & Feng, 2021; Halawi et al., 2005). However, the negative moderation effect explained in this study is consistent with the scenario concerned with contingency theory and is particularly appropriate based on the complexly situated environment that characterizes AI adoption (Nassou & Bennani, 2024). Leadership models that comprehend the dimensions of control and risk avoidance may function as those mechanisms that impede innovation within a resource-restricted environment like Palestine. This idea stresses the extensibility and adaptability of a situation in the specific organization within which it is embedded (Nassou & Bennani, 2024) Furthermore, the Technical Leadership Gap limits effective decision-making on technical issues surrounding AI adoption. This entails the possible absence of technical-related knowledge among top strategic leaders, especially in an evolving discipline like AI (Figueroa et al., 2020). To illustrate more, the Technology

Acceptance Model (TAM), which also finds a negative moderation prevailing in leadership for adoption vis-a-vis pure technique resources, supports explaining the negative moderation effects identified (Omoniyi Babatunde Johnson et al. 2024). These viewpoints affirm Mintzberg's theory whereby strategy is gradually formed through the conflict of goals and their adaptations to the reality that keeps changing. Traditional ideas of leadership generally impede AI adoption more than they enhance it in a rapidly changing segment like that. It resonates with Mintzberg's view that strategy formation is a very complex process that requires being adaptive (Tian et al., 2023; YOLSAL, 2020).

Conversely, Strategic Leadership demonstrated a **positive moderating effect** on the relationship between ICT Information Systems (ICT-S) and ICT People (ICT-P) with AI adoption, as indicated by $\beta = 0.114$, $t = 2.991$, $p=0.001$ and $\beta = 0.129$, $t = 2.709$, $p=0.003$ respectively. These results suggest that leadership positively enhances the alignment of software systems with strategic objectives and fosters a culture of innovation through the development of human capital. This is consistent with Peter Drucker’s emphasis on the importance of knowledge workers and their contributions to technological innovation (Turriago-Hoyos et al., 2016; Kochkina et al., 2024).

The findings also support the Knowledge-Based View on the strategic importance of people and knowledge-based resources for competitive advantage (Hiranphaet et al., 2020). If investment in education, skill development, and innovative organizational culture is given, the leaders will be able to maximize the full potential of ICT and AI technologies (Brillianto et al., 2024). Furthermore, this is very important in the case of the Palestinians, where MSMEs can counter the shortage of physical and other resources with skilled labor and strategically aligned software systems (Musleh, 2022; Pires & Stanton, 2005).

Strategic leadership would also help by emphasizing skill development and creative use of whatever technology is available to Palestinian MSMEs to mitigate some of the hardware and infrastructure constraints. This is reinforced by SL's positive moderating effect on such software and human resource factors (Boal and Hooijberg, 2001; Fourie & Jacob Fourie, 2007; Khalid Thaher Amayreha*, 2020; Mjaku & c, 2020; O'Shannassy, 2021; Tarisayi, 2024)

Palestinian MSMEs need to adopt a balanced approach that considers both the technical and human aspects of technological innovation. This may involve developing a "T-shaped," where the concept refers to a skills profile characterized by deep expertise in a specific area (the vertical bar of the T) combined with a broad understanding across multiple disciplines (the horizontal bar). This model is increasingly relevant in various fields, including technical education, knowledge work, and design engineering, as it prepares individuals for complex, interdisciplinary environments (Saukkonen & Kreus, 2024). Accordingly, leaders can combine broad strategic knowledge with deep technical expertise, as described by Hansen and von Oetinger(Dekoninck & Bridge, 2023) Furthermore, the findings suggest the need for a holistic approach to AI adoption (Yaiphabi Laishram et al., 2024), considering all ICT factors and their interactions with SL. Strategic resource allocation becomes crucial, with leaders in Palestinian MSMEs potentially needing to reconsider resource distribution across different ICT factors.

5.4 Perceived attributes of innovation, ICT Readiness, and AI Adoption

The results of this study provide robust evidence supporting the hypothesis (**H3**) that perceived: attributes of innovation, specifically Relative Advantage (RA) and Compatibility (CO), moderate the relationship between ICT Readiness (ICT-R) factors and AI Adoption (AI-A). With a significant positive moderating effect (β = 0.146, t = 2.784, p = 0.003), the findings indicate that organizations that perceive their ICT systems as offering clear benefits and aligning well with existing practices experience a stronger relationship between ICT-R and AI. These results align with a study on AI adoption in Indian B2B SMEs confirmed that AI enablers, including perceived benefits and trust, significantly impact AI readiness(Polisetty et al., 2023). The findings extend the Diffusion of Innovation (DOI) theory by demonstrating the moderating roles of Relative Advantage and Compatibility in the relationship between ICT readiness and AI adoption (Rogers et al., 2003). They also contribute to the Resource-Based View (RBV) by emphasizing that the perceived value and alignment of ICT systems are essential for leveraging these resources effectively (Barney, 1991). Moreover, the results back the Technology Acceptance Model (TAM), which lays stress on two important factors: perceived ease of use and usefulness—those that relate closely to Compatibility and Relative Advantage—with technology adoption motivations (Davis et al., 1989). Along similar lines, for Palestinian MSMEs, it is significantly more derived from perceived attributes of the innovation. Previous studies on Palestinian MSMEs show that ICT readiness, along with innovation attributes perceived by the user, acts mutually towards AI technology adoption, consistent with findings derived here (Mujahed et al., 2024).

Relative Advantage significantly enhances the relationship between all ICT readiness factors (Infrastructure, Hardware, Information Systems, and People) and AI adoption. The analysis reveals consistent positive moderating effects across sub-hypotheses (H3a–H3d), with path coefficients ranging from β = 0.033 to β = 0.053 and statistically significant results (e.g., t = 2.543 to 2.529, $p < 0.05$). On the contrary, it is opening a new dawn in reckoning wherein available benefits concerning ICT investments are normally proven benefits such as efficiency, cost reduction, or innovation. These have encouraged effective applications and use of AI over ICT investments. Such as in ICT Information Systems (H3c) shows the strongest positive moderation (β = 0.053), reiterating variances in theoretical software systems and improvements in perceived organizational benefits. Earlier studies also extol the pivotal role that perceived relative advantage plays in influencing technology adoption through better user acceptance and alignment within the organization (Masod & Zakaria, 2024b;Ustabaşı, 2024).

The moderating effect of Compatibility is even stronger, with significant positive results across all ICT readiness factors (H3e–H3h). Path coefficients range from $\beta = 0.237$ for ICT Hardware (H3f) to $\beta = 0.377$ for ICT Information Systems (H3g), with extremely high statistical significance (e.g., $t = 22.269$ to 31.009, $p < 0.001$). These findings suggest that the perceived alignment of ICT systems with organizational values, workflows, and needs significantly strengthens the link between ICT readiness and AI adoption. Compatibility is particularly crucial for ICT Information Systems (H3g) and ICT People (H3h), indicating that seamless integration of technology with existing processes and alignment with human resource strategies drive successful AI implementation. These results are consistent with studies emphasizing that compatibility reduces resistance to technological change and fosters smoother transitions in technology adoption processes (Hornor, 2007; Ustabaşı, 2024). These findings are further supported by successful implementations in the education sector, where AI-enabled adaptive learning platforms, compatible with traditional teaching practices, enhance outcomes (Luo, 2023).

5.5 Contribution and Implications

This study has made great theoretical and practical contributions to understanding ICT readiness, strategic leadership, and AI adoption among Palestinian MSMEs that face socioeconomic obstacles as well as cultural peculiarities. It lays a great basis for studying technology adoption in resource-constrained situations by closing the gaps in existing knowledge and providing practical findings in such situations.

5.5.1 Implications for Practice

The findings of this study have several implications for Palestinian MSMEs in the adoption of AI. These ramifications mainly concern contexts with unique cultural features along with specific socioeconomic challenges.

- **Holistic ICT Strategy Development**

First, the Palestinian MSMEs should develop a master ICT strategy consisting of all constructs such as hardware, software, infrastructure, and human resources in preparation for ICT readiness. Such a full approach will also involve operational readiness support requirements based on infrastructure upgrading on a reliable network and cloud computing capacity with hardware modifications that fit the environment for AI algorithm processing and data-intensive applications. Software integration includes the integration of AI platforms that will improve operational efficiency as prerequisites to the successful operation of the current business process. Ultimately, MSMEs need to finance initiatives for employees' data literacy and defining skills for AI. It is the resolution of these issues that will build strong foundations for the adoption of artificial intelligence and innovation for extensive sustainability in the Palestinian MSME sector.

- **Strategic Leadership Development**

Second, the study underscores the complex role of Strategic Leadership in AI adoption, emphasizing the need for a nuanced approach to leadership development. Organizations should focus on developing "T-shaped" executives who would be expected to possess deep technical experience in AI and related technologies and wide strategic knowledge to successfully negotiate the nexus between strategy and technical innovation. Filling the gap in technical leadership would also require the improvement of technical skills, especially in AI-related decision-making, through concerted leadership training programs. It is important to promote adaptive leadership modes. Employees should be flexible and sensitive to the very fast-changing environment that is the AI influenced. Equally, a training program should consider the leaders about the wise allocation of resources and the investment level on human capital development versus tangible investments in ICT. It is with these that organizations may make leaders capable of successfully steering AI adoption but at the same time maximizing organizational resilience and creativity.

- **Innovation Perception Management**

Third, thereby the highlighted significant moderating impact of the perceived attributes of innovation that will place greater emphasis on effective communication and perception management techniques in consideration for the successful adoption of AI. Organizations need to convey the very unique benefits and competitive advantages clearly to ensure that all the stakeholders have a common understanding of the value AI brings. They must also add to this compatibility by making necessary provisions to adopt the smooth integration of AI technologies with existing systems and procedures without compromising the capacity to strengthen rather than disturb operations. Initiating pilot activities is another very important intervention. The small-scale activities can yield tangible evidence of the benefits of AI and, thus, cultivate confidence among management and staff. Finally, an innovation culture is a sine qua non for achieving long-term success: companies, therefore, must create an environment conducive to innovation and open to the adoption of new technology. When piled into these strategies, most of them would create a real revolution in the perception and acceptance of AI in organizations.

- **Resource Optimization**

Fourth, Successful AI implementations are completely dependent on the proper resource allocation and use. This is truer in the case of Palestinian MSMEs. Organizations can, therefore, benefit from high-impact areas using cloud-based AI services, because these applications will give them adequate priority to choose the most advantageous functions of AI according to the resources that can be allocated. Organizations can use cloud-based AI services that allow scalability and flexibility without requiring substantial on-premises equipment for reduced infrastructure costs. Sharing resources with fellow MSMEs or knowledge institutions also improves resource use while allowing for knowledge transfer and sharing of access to AI tools. MSMEs can be bold and look for other external funding options such as grants, government support, or venture capital initiatives designed especially to encourage the adoption of AI. In this way, trying to cross those operational and financial barriers, MSMEs will adopt and integrate AI technologies more successfully and sustainably using these methods.

- **Cultural Adaptation of AI Implementation**

Fifth, MSMEs had to revise their AI adoption strategies to match the local patterns and values of the specific culture to which survey participants belonged, that is, Palestine. Localizing an AI solution is the process of modifying apps for local languages, cultures, and business practices to make sure that it is suitable and useful. Ethical issues would also include the development of clear guidelines for the ethical application of AI, which are in harmony with social norms and cultural sensitivity, build trust, and conform to local expectations. The involvement of local stakeholders, such as business associations and community figures, should also encourage confidence and improve acceptance of MSMEs' campaigns for adopting AI. Promoting local AI talent is also important; through partnerships with academic institutions, businesses could develop a workforce that is knowledgeable about both cutting-edge AI technologies and the unique requirements of the local environment. Together, these tactics guarantee that the adoption of AI is not only technologically successful but also broadly accepted and culturally relevant.

- **Government's Role in AI National Strategy**

Sixth, implementing a national comprehensive strategy on artificial intelligence will leave the Palestinian government as a mediator for AI adoption. The course should also be aligned with the national economic goals while addressing specific challenges faced by MSMEs. The regulation has to develop support frameworks for encouraging AI uptake, resolving moral dilemmas, and addressing data privacy related to the Palestinian context to foster an enabling environment.

Establishing AI innovation hubs is another important thing that enables MSMEs access to resources, human capital, and advanced academic innovations in AI. These will be acting as development and collaboration hubs for the innovation process across a number of sectors. The government can also provide tax incentives, grants, and subsidies to offset financial entry barriers in order to entice MSMEs into AI technologies and training programs.

Such infrastructure becomes key in establishing sustainable inroads towards AI. Hence, large investments will transform both cloud computing infrastructure and fast internet into reliable connectivity to support broad-based AI integration in the early stages. Through these steps, now the Palestinian government can put a strong ecosystem in place that stimulates innovation, lifts the MSMES, and accelerates the economy in an AI age.

- **Higher Education Institutions' Role**

Seventh, universities create necessary access to skills and knowledge, and, indeed, apply AI to empower the people and businesses. Graduate and undergraduate programs need to be structured with an AI focus as part of the preparation for the competent workforce that can lead in practicing innovation with AI. In-depth coverage of primary subjects such as data science, machine learning, and AI ethics must also be included in these programs to ensure thorough training.

Establish a partnership between the academic institutions and the local and foreign IT companies to bridge the academic difference from the industry. Such partnerships would furnish real-world application of AI to the students while aligning the curriculum with industry demands and providing worthwhile internship opportunities.

The establishment of centers for AI research in institutions of learning can trigger more innovations and serve as a resource for MSMEs by providing them with technical assistance and advisory services. Ongoing education programs, like workshops and short courses, should also be offered by universities to help professionals and MSME owners in areas that specifically need more knowledge and understanding of AI issues.

Promoting entrepreneurship in becoming active in an AI-driven economy has a take-off. Universities can launch interventions that can, among other things, create prizes for AI businesses and access to funding, incubators, and mentoring. These schemes can also be effective in developing an environment that encourages the thriving of an emerging economy in which AI is innovated and adopted across industries.

- **Collaborative Ecosystem Development**

Finally, the encouragement of AI research and adoption across industries requires a context for the building of a strong collaborative ecosystem. Government-university partnerships to create AI accelerators could help provide AI-centric firms with the resources, capital, and mentorship for grooming, and growth centers of activity could also serve the potential as potential incubators for entrepreneurial talent and technological progress.

The talent development pipeline for AI is just as critical. Governments, academic institutions, and businesses could work together to set up internship and apprenticeship programs that would give students and recent graduates exposure and hands-on experience in preparation to become contributors to executing AI-oriented projects. Moreover, the establishment of a government-sponsored AI innovation fund with a university component would bring funding to promising research initiatives and entrepreneurs in the field, thus boosting growth and innovations in the AI domain.

Regular AI challenges and hackathons together would further strengthen the ecosystem by bringing students, academia, and MSMEs closer to real-world issues. These gatherings foster collaboration, innovation, and real-life applicability of AI uncover technologies. The last guarantees learning for life and the proliferation of sound techniques by putting in place such venues that would exchange case studies and best practices within MSMEs, scholars, and government institutions.

5.5.2 Implications for Future Research

Based on the findings and limitations of this study, several avenues for future research emerge. These recommendations aim to deepen our understanding of AI adoption in Palestinian MSMEs and similar contexts.

- **Longitudinal Studies on AI Adoption**

Future research should adopt a longitudinal approach to comprehensively track the evolution of AI adoption in Palestinian MSMEs over time, offering valuable insights into its dynamic processes. Such studies could elucidate the long-term impact of ICT Readiness on both AI adoption and business performance, providing a deeper understanding of how foundational technological capabilities shape outcomes. Moreover, they would enable the analysis of changes in the moderating effects of Strategic Leadership as organizations advance in their AI capabilities, highlighting shifts in leadership roles and strategies over time. Additionally, the evolution of Perceived Attributes of Innovation, as AI technologies become more widely adopted, could be examined to understand how perceptions influence acceptance and integration in diverse contexts. By capturing these temporal changes, longitudinal studies would offer a nuanced and dynamic perspective on the relationships between these variables, significantly enriching the understanding of AI adoption processes.

- **Cross-Cultural Comparative Studies**

Such an international comparative study may look at the similarities and differences between Palestinian MSMEs and those of other developing countries regarding AI adoption. Such studies will be able to illuminate specific socioeconomic and cultural elements as influencing factors for technology adoption and identify specific challenges and opportunities within the Palestinian context, which will render more Eastern-focused models of technology adoption. In this way, the research could be made more complex and attuned to the different cultural factors that are encountered in different contexts. Moreover, it is here that such comparative illuminations go a long way in indicating the degrees of generalizability of findings, leading again to region-leveraged methodologies in successful AI integrations. Hence, such research would improve relevance and applicability in diverse developing contexts of frameworks for technology adoption.

- **In-Depth Analysis of Strategic Leadership**

Futuristic exploration in the area of Strategic Leadership would unravel the complex moderating effects that this study has discovered, which might lend a better understanding of knowledge related to Strategic Leadership's effects on AI adoption. In this regard, it will be worthwhile to investigate the leadership behaviors that facilitate AI assimilation, ascertain the attributes and behaviors that lead to positive outcomes, and, most importantly, identify the factors causing the reported negative moderating effect on the relationship between hardware and infrastructure interaction factors; these would, indeed, be very important clues of possible barriers and/or challenges. Finally, analyzing how leadership styles have evolved in light of AI integration would also be relevant, as it could further illuminate how leaders adapt to technological advancements. In-depth understanding would also come from qualitative studies on leadership decision-making processes surrounding AI adoption, thus enriching the theoretical and applied knowledge that relates to this field.

- **Sector-Specific AI Adoption Studies**

Future research should be directed to study the unique sectoral specificities of Palestinian MSMEs with respect to different trends and challenges in the application of AI in other countries. The examination of such differences would facilitate the development of specific implementation plans for AI in the sectors critical to the Palestinian economy, reflecting the reality of every sector's special needs and dynamics. Such studies would also serve to examine the industrial-specific national characteristics, ICT preparedness, and strategic leadership, as well as how these three aspects interact to demonstrate how they affect AI adoption overall. Thus, this method would provide focused and relevant information to politicians and business executives trying to locate strategic and financially appropriate avenues for AI integration.

- **Impact of External Factors on AI Adoption**

To truly understand how AI is being adopted in Palestine, the research must expand beyond just domestic factors. Future research can best assess the positive and negative impacts of legal and regulatory measures on the introduction of AI and identify areas in which integration can be hastened through supportive frameworks. Partnerships also address the access gap in knowledge and technology, so it will be very interesting to explore how international partnerships and knowledge transfer may boost AI capabilities. Finally, exploring how geopolitics affects access to AI knowledge and technology may provide new insights into foreign possibilities and constraints. Taken as a whole, such research would comprise a comprehensive understanding of external pressures on AI within Palestinian MSMEs while providing clear guidance to stakeholders and policymakers.

Conclusion and Summary

This study provides significant insights into the determinants of AI adoption among Palestinian MSMEs, focusing on the interplay between ICT readiness, strategic leadership, and perceived attributes of innovation. The findings reveal that ICT readiness, including the hardware, software, infrastructure, and human resources forms the base on which successful AI implementation can be built Further, these organization and technological characteristics are such that they facilitate the uses of AI by organizations when integrated with stakeholder adoption. Last but not least, perceived innovative traits such as relative advantage and compatibility add to the strength of the association between ICT-R and AI adoption (AI-A), indicating that AI technology should be matched with organizational needs and processes.

Strategic leadership will impact AI adoption through several complicated pathways. Good leadership enhances creativity, rare resource configuration, and effective ICT-R with AI-A interaction. In resource-hungry contexts, however, an overly controlling managerial style amplifies barriers unintentionally. This dual feature accentuates the importance of context-specific, flexible leadership in the scarce-resource environments of Palestine.

Results in the study are specifically applicable to the Palestinian context. Adoption of technology is hampered mainly by sociopolitical hurdles, fragmented communication, and limited access to resources. Against this, results show that specific strategies such as upgrading ICT preparedness, creating favorable dispositions toward advancements in AI, and adopting adaptive leadership stand to benefit Palestinian MSMEs.

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Appendices

Appendix (A) Result of Normality

									Kolmogorov-Smirnov[a]		Shapiro-Wilk	
Con.	**Var.**	**Q#**	**N**	**Missing**	**Skewness**	**Std. Error of Skewness**	**Kurtosis**	**Std. Error of Kurtosis**	**Statistic**	**Sig.**	**Statistic**	**Sig.**
PAI	**RA**	Q1	520	0	0.279	0.107	-1.299	0.214	0.202	0.000	0.866	0.000
		Q2	520	0	0.308	0.107	-1.066	0.214	0.198	0.000	0.890	0.000
		Q3	520	0	0.230	0.107	-1.212	0.214	0.189	0.000	0.886	0.000
		Q4	520	0	0.168	0.107	-1.271	0.214	0.168	0.000	0.883	0.000
		Q5	520	0	0.155	0.107	-1.249	0.214	0.190	0.000	0.889	0.000
		Q6	520	0	0.322	0.107	-1.193	0.214	0.214	0.000	0.875	0.000
		Q7	520	0	0.327	0.107	-1.102	0.214	0.195	0.000	0.885	0.000
	CO	Q8	520	0	0.382	0.107	-1.180	0.214	0.239	0.000	0.867	0.000
		Q9	520	0	0.207	0.107	-1.267	0.214	0.196	0.000	0.883	0.000
		Q10	520	0	0.327	0.107	-1.084	0.214	0.200	0.000	0.887	0.000
		Q11	520	0	0.298	0.107	-1.239	0.214	0.203	0.000	0.875	0.000
AI-A		Q12	520	0	0.299	0.107	-1.196	0.214	0.200	0.000	0.880	0.000
		Q13	520	0	0.289	0.107	-1.172	0.214	0.200	0.000	0.883	0.000
		Q14	520	0	0.127	0.107	-1.226	0.214	0.170	0.000	0.892	0.000
		Q15	520	0	0.182	0.107	-1.080	0.214	0.187	0.000	0.903	0.000
ICT-R	**ICT-I**	Q16	520	0	0.301	0.107	-1.237	0.214	0.209	0.000	0.869	0.000
		Q17	520	0	0.207	0.107	-1.247	0.214	0.180	0.000	0.881	0.000
		Q18	520	0	0.307	0.107	-1.102	0.214	0.211	0.000	0.889	0.000
		Q19	520	0	0.370	0.107	-1.048	0.214	0.208	0.000	0.884	0.000
	ICT-H	Q20	520	0	0.280	0.107	-1.285	0.214	0.208	0.000	0.872	0.000
		Q21	520	0	0.334	0.107	-1.081	0.214	0.190	0.000	0.884	0.000
		Q22	520	0	0.352	0.107	-1.057	0.214	0.221	0.000	0.887	0.000
	ICT-S	Q23	520	0	0.333	0.107	-1.042	0.214	0.202	0.000	0.890	0.000
		Q24	520	0	0.420	0.107	-1.092	0.214	0.205	0.000	0.870	0.000
		Q25	520	0	0.160	0.107	-1.308	0.214	0.200	0.000	0.882	0.000
		Q26	520	0	0.219	0.107	-1.124	0.214	0.170	0.000	0.893	0.000
	ICT-P	Q27	520	0	0.346	0.107	-1.134	0.214	0.209	0.000	0.880	0.000
		Q28	520	0	0.185	0.107	-1.203	0.214	0.187	0.000	0.892	0.000
		Q29	520	0	0.060	0.107	-1.200	0.214	0.150	0.000	0.895	0.000
		Q30	520	0	0.436	0.107	-1.121	0.214	0.235	0.000	0.865	0.000
SL		Q31	520	0	0.288	0.107	-1.248	0.214	0.204	0.000	0.875	0.000
		Q32	520	0	0.342	0.107	-1.142	0.214	0.190	0.000	0.877	0.000
		Q33	520	0	0.341	0.107	-1.163	0.214	0.214	0.000	0.876	0.000
		Q34	520	0	0.254	0.107	-1.252	0.214	0.191	0.000	0.878	0.000
		Q35	520	0	0.328	0.107	-1.094	0.214	0.223	0.000	0.887	0.000
		Q36	520	0	0.332	0.107	-1.226	0.214	0.225	0.000	0.870	0.000
		Q37	520	0	0.257	0.107	-1.270	0.214	0.199	0.000	0.876	0.000

Appendix (B) Cross Loading Result

Var.	Q#	AI-A	CO	PAI	ICT-R	ICT-H	ICT-I	ICT-P	ICT-S	RA	SL
RA	Q1	0.534	0.510	0.643	0.581	0.447	0.568	0.514	0.488	0.665	0.586
	Q2	0.504	0.489	0.638	0.540	0.440	0.507	0.440	0.493	0.672	0.528
	Q3	0.621	0.546	0.696	0.618	0.563	0.519	0.522	0.562	0.720	0.582
	Q4	0.549	0.618	0.731	0.644	0.574	0.551	0.570	0.560	0.739	0.639
	Q5	0.523	0.546	0.663	0.566	0.487	0.489	0.496	0.505	0.676	0.583
	Q6	0.540	0.537	0.691	0.581	0.504	0.541	0.496	0.491	0.723	0.579
	Q7	0.556	0.529	0.661	0.567	0.478	0.496	0.478	0.526	0.679	0.554
CO	Q8	0.534	0.733	0.643	0.585	0.479	0.491	0.553	0.513	0.534	0.544
	Q9	0.460	0.700	0.629	0.536	0.512	0.420	0.489	0.464	0.539	0.533
	Q10	0.549	0.712	0.672	0.585	0.496	0.518	0.530	0.495	0.590	0.578
	Q11	0.547	0.780	0.706	0.619	0.501	0.526	0.559	0.567	0.603	0.588
AI-A	Q12	0.670	0.522	0.531	0.511	0.423	0.446	0.440	0.469	0.490	0.451
	Q13	0.741	0.509	0.618	0.614	0.489	0.555	0.558	0.533	0.629	0.590
	Q14	0.681	0.484	0.523	0.487	0.396	0.417	0.424	0.457	0.500	0.491
	Q15	0.738	0.517	0.597	0.539	0.441	0.454	0.489	0.491	0.592	0.635
ICT-R	Q16	0.447	0.494	0.561	0.597	0.442	0.689	0.497	0.443	0.552	0.582
	Q17	0.477	0.477	0.561	0.661	0.488	0.742	0.534	0.531	0.563	0.569
	Q18	0.434	0.376	0.455	0.582	0.456	0.689	0.466	0.416	0.462	0.488
	Q19	0.529	0.552	0.592	0.694	0.541	0.732	0.614	0.521	0.565	0.554
ICT-H	Q20	0.478	0.548	0.604	0.681	0.768	0.561	0.557	0.539	0.586	0.585
	Q21	0.435	0.455	0.509	0.609	0.701	0.494	0.486	0.491	0.497	0.497
	Q22	0.467	0.506	0.539	0.589	0.760	0.448	0.484	0.420	0.514	0.547
ICT-S	Q23	0.469	0.509	0.543	0.647	0.490	0.505	0.520	0.736	0.516	0.510
	Q24	0.486	0.554	0.584	0.625	0.494	0.488	0.441	0.753	0.551	0.498
	Q25	0.595	0.543	0.618	0.671	0.504	0.511	0.535	0.769	0.609	0.551
	Q26	0.421	0.387	0.452	0.521	0.382	0.426	0.391	0.605	0.452	0.420
ICT-P	Q27	0.582	0.617	0.627	0.725	0.566	0.609	0.773	0.562	0.578	0.596
	Q28	0.414	0.437	0.444	0.582	0.444	0.457	0.671	0.447	0.409	0.470
	Q29	0.394	0.472	0.508	0.534	0.410	0.405	0.655	0.382	0.488	0.466
	Q30	0.534	0.553	0.607	0.703	0.539	0.636	0.770	0.492	0.587	0.614
SL	Q31	0.464	0.444	0.506	0.524	0.452	0.490	0.456	0.434	0.498	0.628
	Q32	0.483	0.425	0.488	0.505	0.461	0.460	0.480	0.369	0.485	0.683
	Q33	0.551	0.538	0.572	0.554	0.486	0.511	0.499	0.440	0.543	0.672
	Q34	0.634	0.646	0.689	0.652	0.581	0.571	0.584	0.543	0.655	0.771
	Q35	0.494	0.488	0.596	0.545	0.458	0.472	0.492	0.479	0.607	0.658
	Q36	0.418	0.497	0.545	0.550	0.515	0.512	0.484	0.419	0.528	0.612
	Q37	0.548	0.545	0.602	0.627	0.492	0.600	0.538	0.551	0.583	0.672

Appendix (C) Research Questionnaire English Version

Welcome to Study

Section A: Background Information

Dear respondent,

In your hands is a questionnaire distributed by a Ph.D. student in the Strategic Management program at the School of College of Graduate Studies - Arab American University of Palestine. The study topic is:

“Artificial Intelligence Adoption and Implementation in Palestinian Context: The Moderating Role of Strategic Leadership and the Perceived Attributes of Innovation”

The purpose of this dissertation is to investigate the relationship between information and communication technology (ICT) readiness, strategic leadership, perceived innovation attributes, and artificial intelligence (AI) adoption in Palestinian institutions. The research aims to fill the knowledge gap in AI adoption among developing countries, specifically Palestine, and provide insights to organizations and institutions to guide policy and decision-making by stakeholders.

Completing the questionnaire is expected to consume approximately 10-15 minutes of your time, and the gathered information will contribute to academic research. Your participation is entirely anonymous, and there is no need to provide your name. The compiled data will be presented solely as summary statistics. Your involvement in this survey is optional, and you can refrain from answering any questions. Your participation is greatly valued, as your input will significantly contribute to the study's findings.

If you have any inquiries concerning the research or the questionnaire, please don't hesitate to reach out to the researcher at the provided mobile number: 00972-528198481.

E-mail: e.nabhan@student.aaup.edu
Elham Nabhan
Arab American University

Thanks for your cooperation and time

Section B: Socio-demographic Information

Please fill in the following:

1. Gender:

( ) Male
( ) Female

2. Job Description:

( ) General Manager CEO/Director
( ) Production Executive/Manager
( ) Marketing/Purchasing/Sales Executive/Manager
( ) Senior Finance and HR Managers
( ) IT Application Manager
( ) IT Infrastructure Manager
( ) IT development manager
( ) Others,_______________

3. Managerial experience:

( ) 1-5 years
( ) 5-10 years
( ) 10-15 years
( ) more than 15 years

4. Age:

( ) 18 to 30
( ) 31 to 44
( ) 45 to 60
( ) More than 60

5. Educational level:

( ) Secondary school
( ) Bachelor's degree
( ) Master's degree
( ) Doctorate degree
( ) Others,______________

6. Years of experience in implementing or using Artificial Intelligence technologies.

( ) None
( ) Less than 2 years
( ) 2 years to less than 5 years
( ) 5 years or more

7. Sector of work in the organization/Firm:

( ) Industrial sector
( ) Telecommunication and information
( ) Transport and Storage
( ) Construction
( ) Internal trade /E-commerce
( ) Services(Education, Healthcare, Marketing, Electricity, etc)
( ) Others, __________

8. Number of employees in the organization:

( ) 1-4
( ) 5-19
( ) 20-49
( ) 50 over

Section C: Questionnaire Axes

Please circle or highlight the number which reflects your level of agreement. (Strongly Disagree=1, Disagree=2, Neutral=3, Agree=4, and Strongly Agree=5).

Dimension	#	Indicators	Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
Perceived Attributes of Innovation -Relative Advantage							
Relative Advantage	1.	Adopting Artificial Intelligence will allow better communication with customers.					
	2.	Adopting Artificial Intelligence will increase profitability.					
	3.	Adopting Artificial Intelligence will reduce costs.					
	4.	Adopting Artificial Intelligence will allow us to enter new businesses or markets.					
	5.	Adopting Artificial Intelligence will improve the web presence.					
	6.	Adopting Artificial Intelligence will increase productivity.					

	7.	Adopting Artificial Intelligence will increase flexibility.					
Compatibility	8.	The adoption of Artificial Intelligence is consistent with organizational beliefs and values in my industry sector.					
	9.	The attitude towards Artificial Intelligence adoption in organizations in my industry sector is favorable.					
	10.	The adoption of Artificial Intelligence is generally compatible with Information technology (IT) infrastructure.					
	11.	Adoption of Artificial Intelligence is consistent with the business strategy.					
AI Adoption							
AI Adoption	12.	I am aware of AI implementation in my organization.					
	13.	My industry has a positive outlook towards AI.					
	14.	AI has created an impact on the industry.					
	15.	I would consider adopting AI in my project or line of business.					
ICT Readiness Assessment							
ICT Infrastructure	16.	To what extent do you agree that your organization has adequate general rooms and electric power systems to support its ICT infrastructure?					
	17.	To what extent do you agree that your organization has an effective management policy for its physical ICT infrastructure?					
	18.	To what degree do you agree that your organization has adequate network infrastructure, including local area networks, and wide area networks data center to support its ICT operations?					
	19.	How much do you agree that your organization implements effective network security measures, such as firewalls and intrusion detection systems?					

ICT Hardware	20.	To what extent do you agree that your organization provides an adequate number of personal ICT devices (such as personal computers, printers, scanners, and other hardware) for each employee to effectively perform their duties?					
	21.	To what extent do you agree that your organization has adequate private servers for internal usage and data storage to support its operations?					
	22.	To what extent do you agree that your organization has adequate servers for external usage to support its operations and interactions with external stakeholders?					
ICT Software and Systems	23.	To what extent do you agree that your organization has adequate core business software, general support software, and knowledge handling software?					
	24.	How much do you agree that your organization maintains proper software confidentiality, integrity, and documentation (such as manuals and help documents)?					
	25.	To what degree do you agree that your organization has sufficient core and support information systems?					
	26.	How strongly do you agree that your organization provides adequate support for information systems and maintains proper documentation (including manuals and development documents)?					
ICT People and Human Resources	27.	To what extent do you agree that your organization has effective policies to encourage human resource development?					
	28.	How much do you agree that your organization adequately encourages staff improvement through education, examinations, and certifications?					
	29.	To what degree do you agree that your organization effectively manages investment in staff through training plans and seminar schedules?					
	30.	How strongly do you agree that your organization has developed effective knowledge management practices?					
Strategic Leadership Role							
Strategic Leadership Role	31.	Our leaders effectively determine the strategic direction of the organization					
	32.	The leadership establishes balanced organizational controls, considering both financial and non-financial aspects.					

	33.	Our leaders sustain an effective organizational culture.					
	34.	Our leadership consistently emphasizes ethical practices throughout the organization.					
	35.	Our leadership effectively focuses on exploiting and maintaining the organization's core competencies.					
	36.	Leadership prioritizes the development of human capital in our organization.					
	37.	Leadership actively develops social capital within our organization.					

Thanks for your Cooperation

Appendix (D) Research Questionnaire Arabic Version

الملحق أ: الاستبانة

القسم أ: معلومات أساسية

المشاركين الأعزاء،

بين يديك استبيان موزع من قبل طالبة دكتوراه في برنامج الإدارة الاستراتيجية في كلية الدراسات العليا - الجامعة العربية الأمريكية في فلسطين. موضوع الدراسة هو:

"تبني وتطبيق الذكاء الاصطناعي في السياق الفلسطيني: الدور المعتدل للقيادة الاستراتيجية والسمات المدركة للابتكار".

الغرض من هذه الأطروحة هو دراسة العلاقة بين جاهزية تكنولوجيا المعلومات والاتصالات (ICT Readiness)، والقيادة الاستراتيجية، والسمات المدركة للابتكار(الميزة النسبية والتوافق)، وتبني الذكاء الاصطناعي (AI) في المؤسسات الفلسطينية. يهدف البحث إلى سد الفجوة المعرفية في تبني الذكاء الاصطناعي بين الدول النامية، وتحديداً فلسطين، وتقديم رؤى للمنظمات والمؤسسات لتوجيه السياسات وصنع القرار من قبل أصحاب المصلحة.

من المتوقع أن يستغرق إكمال الاستبيان حوالي 10 - 15 دقيقة من وقتكم، وستساهم المعلومات التي سيتم جمعها في البحث الأكاديمي. مشاركتكم ستكون سرية بشكل كامل، ولا حاجة لذكر اسمكم أو مكان عملكم. سيتم تقديم البيانات المجمعة في صورة إحصاءات ملخصة فقط. إن مشاركتكم في هذا الاستبيان اختيارية، ويمكنكم الامتناع عن الإجابة على أي من الأسئلة.

إن مشاركتكم ذات قيمة كبيرة، حيث إن مدخلاتكم ستساهم بشكل كبير في نتائج الدراسة.

إذا كان لديك أي استفسارات بخصوص البحث أو الاستبيان، فلا تتردد في التواصل مع الباحثة على رقم الهاتف المحمول:

0528198481

البريد الإلكتروني:e.nabhan@student.aaup.edu

إلهام نبهان

الجامعة العربية الأمريكية

شكرًا لتعاونك ووقتك.

القسم ب: المعلومات الاجتماعية والديموغرافية

الرجاء تعبئة الخيار المناسب:

1. **الجنس:**
   ( ) ذكر
   ( ) أنثى

2. **المسمى الوظيفي:**
   ( ) المدير العام / الرئيس التنفيذي
   ( ) مدير الإنتاج
   ( ) مدير التسويق / المشتريات / المبيعات
   ( ) مدير المالية والموارد البشرية
   ( ) مدير تطبيقات تكنولوجيا المعلومات
   ( ) مدير البنية التحتية لتكنولوجيا المعلومات
   ( ) مدير تطوير تكنولوجيا المعلومات
   ( ) أخرى، ____________________

3. **الخبرة الإدارية:**
   ( ) 1-5سنوات
   ( ) 5-10 سنوات
   ( ) 10-15 سنة
   ( ) أكثر من 15 سنة

4. **العمر:**
   ( ) 18 الى 30
   ( ) 31 الى 44
   ( ) 45 الى 60
   ( ) أكثر من 60

5. **المستوى التعليمي:**
   ( ) الثانوية العامة
   ( ) درجة البكالوريوس
   ( ) درجة الماجستير
   ( ) درجة الدكتوراه
   ( ) أخرى، ________________

6. **القطاع الذي تعمل فيه الشركة او المنظمة:**
   ( ) القطاع الصناعي
   ( ) الاتصالات والمعلومات
   ( ) النقل والتخزين
   ( ) البناء
   ( ) التجارة / التجارة الإلكترونية
   ( ) الخدمات(التعليم، الصحة، التسويق، وغيره)
   ( ) أخرى، ________________

7. سنوات خبرتك في تنفيذ أو استخدام تقنيات الذكاء الاصطناعي:
   ( ) لا يوجد
   ( ) أقل من سنتين
   ( ) من سنتين إلى أقل من 5 سنوات
   ( ) 5 سنوات أو أكثر

8. عدد الموظفين داخل المنظمة:
   ( ) 1-4
   ( ) 5-19
   ( ) 20-49
   ( ) 50 أو أكثر

القسم ج: محاور الاستبيان

يرجى وضع دائرة حول الرقم أو تظليله بما يعكس مستوى موافقتك. (لا أوافق بشدة=1، لا أوافق=2، محايد=3، أوافق=4، أوافق بشدة=5).

الأبعاد	رقم البند	المؤشرات	لا أوافق بشدة	لا أوافق	محايد	أوافق	أوافق بشدة
السمات المدركة للابتكار - مؤشرات الميزة النسبية							
الميزة النسبية	1	تبني الذكاء الاصطناعي سيتيح تواصلاً أفضل مع العملاء.					
	2	تبني الذكاء الاصطناعي سيزيد من الربحية.					
	3	تبني الذكاء الاصطناعي سيقلل التكاليف.					
	4	تبني الذكاء الاصطناعي سيسمح لنا بدخول أعمال أو أسواق جديدة.					
	5	تبني الذكاء الاصطناعي سيحسن الحضور على شبكة الإنترنت.					
	6	تبني الذكاء الاصطناعي سيزيد الإنتاجية.					
	7	تبني الذكاء الاصطناعي سيزيد المرونة.					
السمات المدركة للابتكار - مؤشرات التوافق							
التوافق	8	تبني الذكاء الاصطناعي يتوافق مع المعتقدات والقيم التنظيمية في قطاع صناعتي.					
	9	الموقف تجاه تبني الذكاء الاصطناعي في المنظمات في منظمتي إيجابي.					
	10	تبني الذكاء الاصطناعي متوافق بشكل عام مع البنية التحتية لتكنولوجيا المعلومات في المنظمة .					
	11	تبني الذكاء الاصطناعي يتسق مع استراتيجية الأعمال المنظمة.					
مؤشرات تبني الذكاء الاصطناعي							
تبني الذكاء الاصطناعي	12	أنا على دراية بتطبيق الذكاء الاصطناعي في منظمتي.					
	13	لدى المنظمة التي أعمل بها نظرة إيجابية تجاه الذكاء الاصطناعي.					
	14	أحدث الذكاء الاصطناعي تأثيراً في الصناعة.					
	15	سأفكر في تبني الذكاء الاصطناعي في مشروعي أو مجال عملي.					
مؤشرات تقييم الجاهزية لتكنولوجيا المعلومات والاتصالات							
العامل 1- مؤشرات البنية التحتية لتكنولوجيا المعلومات والاتصالات							

					إلى أي مدى توافق على أن منظمتك لديها غرف عامة وأنظمة طاقة كهربائية كافية لدعم بنيتها التحتية لتكنولوجيا المعلومات والاتصالات؟"	16	البنية التحتية لتكنولوجيا المعلومات والاتصالات
					إلى أي مدى توافق على أن منظمتك لديها سياسة إدارة فعالة لبنيتها التحتية المادية لتكنولوجيا المعلومات والاتصالات؟	17	
					إلى أي درجة توافق على أن منظمتك لديها بنية تحتية شبكية كافية، بما في ذلك الشبكات المحلية والشبكات واسعة النطاق ومركز البيانات لدعم عمليات تكنولوجيا المعلومات والاتصالات الخاصة بها؟	18	
					الى أي مدى توافق على أن منظمتك تطبق إجراءات أمنية فعالة للشبكة، مثل جدران الحماية وأنظمة كشف التسلل؟	19	
العامل 2- مؤشرات الأجهزة لتكنولوجيا المعلومات والاتصالات							
					إلى أي مدى توافق على أن منظمتك توفر عددًا كافيًا من أجهزة تكنولوجيا المعلومات والاتصالات الشخصية (مثل أجهزة الكمبيوتر الشخصية والطابعات والماسحات الضوئية وغيرها من الأجهزة) لكل موظف لأداء واجباته بفعالية؟	20	الأجهزة لتكنولوجيا المعلومات والاتصالات
					إلى أي مدى توافق على أن منظمتك لديها خوادم خاصة كافية للاستخدام الداخلي وتخزين البيانات لدعم عملياتها؟	21	
					إلى أي مدى توافق على أن منظمتك لديها خوادم كافية للاستخدام الخارجي لدعم عملياتها وتفاعلاتها مع الأطراف المعنية الخارجية؟	22	
العامل 3 - مؤشرات البرمجيات ونظم المعلومات							
					إلى أي مدى توافق على أن منظمتك تمتلك برمجيات أعمال أساسية كافية، وبرمجيات دعم عامة، وبرمجيات لمعالجة المعرفة؟	23	البرمجيات ونظم المعلومات
					ما مدى موافقتك على أن منظمتك تحافظ على سرية وسلامة البرمجيات والتوثيق المناسب (مثل الأدلة ووثائق المساعدة)؟	24	
					إلى أي درجة توافق على أن منظمتك تمتلك أنظمة معلومات أساسية وداعمة كافية؟	25	
					ما مدى موافقتك بقوة على أن منظمتك توفر دعمًا كافيًا لأنظمة المعلومات وتحتفظ بتوثيق مناسب (بما في ذلك الأدلة ووثائق التطوير)؟	26	
العامل 4 - مؤشرات الأفراد والموارد البشرية							
					إلى أي مدى توافق على أن منظمتك لديها سياسات فعالة لتشجيع تطوير الموارد البشرية؟	27	

الأفراد والموارد البشرية	28	ما مدى موافقتك على أن منظمتك تشجع بشكل كافٍ تحسين أداء الموظفين من خلال التعليم والاختبارات والشهادات؟					
	29	إلى أي درجة توافق على أن منظمتك تدير بفعالية الاستثمار في الموظفين من خلال خطط التدريب وجداول الندوات؟					
	30	ما مدى موافقتك بقوة على أن منظمتك قد طورت ممارسات فعالة لإدارة المعرفة؟					
مؤشرات دور القيادة الاستراتيجية							
القيادة الاستراتيجية	31	يحدد القائد الاتجاه الاستراتيجي للمنظمة بفعالية.					
	32	تضع القيادة ضوابط تنظيمية متوازنة، مع مراعاة الجوانب المالية وغير المالية.					
	33	يحافظ قادتنا على ثقافة تنظيمية فعالة.					
	34	تؤكد قيادتنا باستمرار على الممارسات الأخلاقية في جميع أنحاء المنظمة.					
	35	تركز قيادتنا بفعالية على استغلال والحفاظ على الكفاءات الأساسية للمنظمة.					
	36	تعطي القيادة الأولوية لتطوير رأس المال البشري في منظمتنا.					
	37	تعمل القيادة بنشاط على تطوير رأس المال الاجتماعي داخل منظمتنا.					

Appendix (E) IRB Approval Letter

Arab American University
Institutional Review Board - Ramallah

الجامعــــة العربيــــة الأمريكيــــة
مجلس اخلاقيات البحث العلمي – رام الله

IRB Approval Letter

Study Title: "Artificial Intelligence Adoption and Implementation in Palestinian Context: The Moderating Role of Strategic Leadership and the Perceived Attributes of Innovation".

Submitted by: Elham Mohmmad Abed Nabhan

Date received: 8th November 2024

Date reviewed: 12th November 2024

Date approved: 12th November 2024

Your Study titled **"Artificial Intelligence Adoption and Implementation in Palestinian Context: The Moderating Role of Strategic Leadership and the Perceived Attributes of Innovation"** with the code number **"R-2024/A/159/N"** was reviewed by the Arab American University Institutional Review Board - Ramallah and it was approved on the 12th of November 2024.

الجامعة العربية الأمريكية . فلسطين
مجلس اخلاقيات البحث العلمي . رام الله
IRB-R
ARAB AMERICAN UNIVERSITY-PALESTINE
INSTITUTIONAL REVIEW BOARD - RAMALLAH

Sajed Ghawadra, PhD
IRB-R Chairman
Arab American University of Palestine

General Conditions:

1. Valid for 6 months from the date of approval.
2. It is important to inform the IRB-R with any modification of the approved study protocol.
3. The Bord appreciates a copy of the research when accomplished.

رام الله – فلسطين

Tel: 02-294-1999 **E-Email:** IRB-R@aaup.edu **Website:** www.aaup.edu

الملخص

الغرض: تستكشف هذه الدراسة العلاقات بين عوامل جاهزية تكنولوجيا المعلومات والاتصالات، القيادة الاستراتيجية، وتبني الذكاء الاصطناعي داخل المؤسسات الصغيرة والمتوسطة الفلسطينية. كما تسلط الضوء على الأدوار التعديلية للقيادة الاستراتيجية والسمات المتصورة للابتكار في البيئات ذات الموارد المحدودة.

المنهجية: تم استخدام نهج كمي مقطعي شمل 520 مشاركًا من مؤسسات صغيرة ومتوسطة متنوعة في الضفة الغربية بفلسطين. جُمعت البيانات عبر استبيانات منظمة وحُللت باستخدام PLS-SEM و SPSSلتقييم الفرضيات والتحقق من صحة البُنى.

النتائج: تشير النتائج إلى أن جاهزية تكنولوجيا المعلومات والاتصالات، التي تشمل الأجهزة، البرمجيات، البنية التحتية، والموارد البشرية، تُعتبر عوامل دافعة رئيسية لتبني الذكاء الاصطناعي (β=0.140، t=2.544، p= 0.006) تُظهر القيادة الاستراتيجية تأثيرًا مزدوجًا: حيث تؤثر إيجابيًا على موائمة البرمجيات والموارد البشرية (β=0.114، β=0.129) على التوالي، بينما تعدل سلبًا جاهزية البنية التحتية (β= -0.129) والأجهزة .(β= -0.072) تعزز سمات الابتكار المتصورة، مثل الميزة النسبية والتوافق، من تأثير جاهزية تكنولوجيا المعلومات والاتصالات على تبني الذكاء الاصطناعي(β= 0.146، t=2.784، p=0.003)

التطبيقات العملية: يمكن لصناع السياسات والقادة في البيئات ذات الموارد المحدودة الاستفادة من هذه النتائج لتصميم استراتيجيات شاملة لتكنولوجيا المعلومات والاتصالات، وتعزيز نهج قيادي متوازن، ومعالجة العوائق أمام تبني الذكاء الاصطناعي.

الأصالة: تُسهم هذه الدراسة في الأدبيات المتعلقة بتبني التكنولوجيا من خلال التركيز على سياق سياسي معقد وموارد محدودة، مما يوفر رؤى قابلة للتنفيذ لتعزيز قدرة الابتكار في المؤسسات الصغيرة والمتوسطة عبر تبني الذكاء الاصطناعي

الكلمات المفتاحية: جاهزية تكنولوجيا المعلومات والاتصالات، تبني الذكاء الاصطناعي، القيادة الاستراتيجية، سمات الابتكار، المؤسسات الصغيرة والمتوسطة الفلسطينية، تبني التكنولوجيا، البيئات ذات الموارد المحدودة، التحليل الكمي، PLS-SEM، الاقتصادات النامية.