DETERMINANTS OF ADOPTION AND IMPACT OF DIGITAL TECHNOLOGIES BY SMEs IN JORDAN

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APRIL 2023

DETERMINANTS OF ADOPTION AND IMPACT OF DIGITAL TECHNOLOGIES BY SMEs IN JORDAN

THESIS SUBMITTED IN PARTIAL FULFILLMENT OF THE REQUIREMENT FOR THE DEGREE OF DOCTOR OF PHILOSOPHY

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ABSTRACT

Today's digital technologies, including artificial intelligence, social media networks, big data, sophisticated manufacturing, cloud computing, cyber solutions, and 3D printing, are utilized in many businesses worldwide. While prior studies have examined the acceptance of digital technologies in Western and other advanced nations, few have focused on the Middle East, especially Jordan. Developing countries like Jordan require assistance with numerous challenges, including poor information systems, limited usage, and low usability. Governments and various business sectors must embrace these rapidly advancing digital technologies to remain competitive in today's business world. While many studies have explored the adoption and impact of digital technologies on small and medium-sized enterprises (SMEs), SMEs in developing countries need to be more aware of the benefits of digital technologies. This research investigates the acceptance and impact of digital technologies on SMEs in Jordan. The study addresses a significant knowledge gap by examining the organizational, technological, socio-cultural, political-environmental, and demographic determinants of digital technology adoption that influence Jordanian SMEs' decision-making process. Specifically, the study focuses on Artificial Intelligence (AI) as a critical digital technology. A comprehensive theoretical framework based on several theories and models, including the theory of reasoned action (TRA), technology acceptance model (TAM), diffusion of innovations (DOI) theory, unified theory of acceptance and use of technology (UTAUT), and Technology Organization Environment (TOE) framework, is proposed to provide a comprehensive understanding of digital technology adoption determinants by SMEs in developing countries such as Jordan. The study collects and analyzes data using quantitative methods. Online questionnaires were distributed to all 1600 registered SMEs in Jordan and Amman. Data was collected from owners/managers of Jordanian SMEs in Amman about their attitudes towards accepting and using one type of digital technology, such as AI systems. The data were analyzed using the Statistical Package for Social Sciences 27 (SPSS) and included summary statistics, frequency distribution analysis, reliability tests, correlation analysis, factor analysis, and multiple regression analyses. Of the 401 who responded, 364 were deemed usable, resulting in a response rate of 25%. The study's findings provide valuable insights for SME owners, managers, and policymakers in developing countries to adopt digital technologies and achieve economic growth. The key finding is that embracing digital technologies positively impacts SME performance, with significant positive correlations between digital technology usage and productivity and customer satisfaction. The study also identifies several determinants that influence the adoption of digital technologies, including employees' IT knowledge, technology infrastructure, managerial support, training, reward system, government support, social networks, and religious beliefs. This study's significant contribution provides a solid foundation for developing policies and procedures for implementing digital technologies in SMEs in developing countries and improving their market competitiveness. The study recommends that SME owners and managers be educated on the benefits of digital technologies and that government policies focus on providing access to training and financing, increasing awareness of the benefits of digital technologies, and creating an enabling environment for SMEs to adopt digital technologies. These recommendations can help promote the adoption of digital technologies among SMEs in Jordan and enhance their competitiveness in the global market.

ACKNOWLEDGEMENTS

First and foremost, I thank Allah almighty, the creator of the whole universe, for giving me the strength and time to complete this thesis. This work was completed with the success He gave me.

In writing this thesis, I received gracious help from several individuals without their assistance, support, and advice, this study would have been very challenging. I am grateful and sincere in my appreciation to all of them. I express my profound thanks to my supervisors, Dr Majharul Talukder and Dr Sarvjeet Kaur Chatrath, who provided me with continual assistance, important suggestions, encouragement and informed advice throughout this task. For this, I am very grateful. You always responded quickly, sharing your ideas and helping me to conclude the study on time.

I also want to thank Dr Jennifer Loh, Associate Dean of Research. I also thank Sue Uzabeaga, HDR adviser for her valued assistance and support. You guided my research, provided excellent facilities, and inspired me to overcome obstacles and difficulties. My beloved mother, my wife, and my daughters are to be thanked for their patience, support, prayers, and understanding; inspiration and encouragement were critical in completing this study. They all gave me the strength to succeed in achieving my PhD studies. May Allah Almighty bless you all.

I express my most profound appreciation to the Amman Chamber of Commerce for providing me with all the information I required to embark on and complete this research.

I sincerely thank all the owners and managers of Jordanian SMEs who completed the survey questionnaire for their valuable time and for sharing their experiences. Finally, I thank the University of Canberra's authorities and Faculty of Business, Government & Law for allowing me to study at this unique university and their support in completing my study program.

PUBLICATIONS

The following refereed papers have been developed from the PhD research:

Almashawreh, R., Talukder, M., & Chatrath, S. K. (2021). Determinants of the adoption and impact of digital technologies in SMEs in Jordan. The International Conference on Sustainable Technology and Development. Organized by Elsevier Publishing Company. October 31 - November 3, 2021, Shenzhen, Nanshan, China.

Almashawreh, R., Talukder, M., & Chatrath, S. K. (2022). Impact of political & socio-cultural determinants on users' acceptance of AI in Jordanian SMEs. *IEEE Access*, (In Progress).

Almashawreh, R., Talukder, M., & Chatrath, S. K. (2023). Do technological & organizational orientation influence AI usage by individual employees in SMEs in Jordan. *Business Process Management Journal* (In Progress).

Almashawreh, R., Talukder, M., & Chatrath, S. K. (2023). Investigating the factors affecting the adoption of digital technologies in Jordanian SMEs. Second International Conference on Education, Technology, and Law: Reality and Future, Organized by several universities and organizations. January 28-February 4, 2023, Morocco.

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LIST OF ABBREVIATIONS

AI	Artificial Intelligence
ACC	Amman Chamber of Commerce
AM	Additive Manufacturing
AMTs	Advanced Manufacturing Technologies
AR	Augmented Reality
BIM	Building Information Modelling
BMI	Business Model Innovation
CB	Covariance-Based
CFA	Confirmatory Factor Analysis
CPS	Cyber-Physical Systems
DCO	Digital Cooperation Organization
DOI	Diffusion of Innovations Theory
EDI	Electronic Data Interchange
EFA	Exploratory Factor Analysis
ERP	Enterprise Resource Planning
ICTs	Information and Communication Technologies
IIoT	Industrial internet of things
IoT	Internet of Things
IS	Information Systems
IT	Information Technology
JEDCO	Jordanian Enterprise Development Corporation
KBV	Knowledge-based View
LAS	League of Arab States
MASA	Mesh Applications and Service Architecture
ML	Machine learning
MODEE	Ministry of Digital Economy and Entrepreneurship
MR	Mixed Reality
MSPs	Multi-Sided Platforms
OECD	Organization of Economic Co-operation and Development
PAF	Principal Axis Factoring
PCA	Principal Components Analysis
RBV	Resource-Based View
SCT	Social Cognitive Theory
SEM	Structural Equation Modelling
SF	Smart Factory
SMEs	Small, Medium-sized Enterprises
TAM	Technology acceptance model
TOE	Technology -organization- environment framework
TPB	The Social Cognitive Theory
TPB	Theory of Planned Behavior
TRA	Theory of Reasoned Action
TRI	Technology Readiness Index
UTAUT	Unified Theory of Acceptance and Use of technology
VIF	Variance Inflation Factor

CHAPTER ONE: INTRODUCTION

1.1 Background of the Study

The now widespread reliance on digital technologies has resulted in great changes in how businesses and their staff operate including improved operations and outcomes (Van Veldhoven & Vanthienen, 2021; Oliveira, Kakabadse & Khan, 2022). Advances in digital technologies have generated massive improvements in virtually every aspect of people's lives, including communications, workplace practices, entertainment, travel, banking, shopping, manufacturing industries, and services, etc. (Paiola, Schiavone, Grandinetti & Chen, 2021). Through digital technology, businesses are transforming themselves into more diversified enterprises (Li, Wu, Cao & Wang, 2021). This ability is critical during unexpected economic downturns, political uncertainty, geopolitics, and trade wars (Brosseau, Ebrahim, Handscomb & Thaker, 2019; Lee & Trimi, 2021). There is no one method for estimating the influence of digital technologies, mainly on a corporation's financial and economic qualities, and its effects on the personal, social, and economic paths of a modern society's progress are equivocal (Zemlyak, Gusarova & Khromenkova, 2022).

Digital technologies greatly improve business functioning (Marcucci, Antomarioni, Ciarapica & Bevilacqua, 2021; Wu, Lee & Tian, 2021; Oliveira, Kakabadse & Khan, 2022). The acceptance of new technology is a key driver of firm performance and economic development (Delera, Pietrobelli, Calza & Lavopa, 2022). Creating a digital workplace is about altering personal, team, and organizational performance, not simply about using emails and social media or integrating digital tools (Dressler & Paunovic, 2021). However, the performance gains are frequently obstructed by people's unwillingness to use and adapt technology innovations (Talukder, 2014; Fernandes & Oliveira, 2021). Because this issue is still significant and can be a fundamental barrier to adoption, it has been a long-term concern of researchers to explain how people adopt and use new technology, or not (Talukder, 2014; Hsu & Lin, 2016; Chi, Denton & Gursoy, 2020; Fernandes & Oliveira, 2021). Researchers and practitioners stressed the importance of better understanding the determinants, expanded dimensionalities and focus on users' motivations to accept an innovation in the workplace

(Sherif, Zmud & Browne, 2006; Venkatesh, Morris & Ackerman, 2000; Talukder, 2014; Lin, Chi & Gursoy, 2020; Fernandes & Oliveira, 2021).

There is a consensus that digital technologies do significantly drive firms into new business models, reduce costs, and people working without a physical environment (Fjeldstad & Snow, 2018; Westerlund, 2020; Mohamed & Weber, 2020; Dutta, Kumar, Sindhwani & Singh, 2020; Zide & Jokonya, 2022). Changes have been occurring in digital technologies and digital infrastructure over the past few decades with new marketing models, business processes, and organizational cultures, and small, medium-sized enterprises (SMEs) are not exempt from this trend (Dethine, Enjolras & Monticolo, 2020). Small businesses must be more innovative in all aspects of their operations, including marketing, work planning, financing, development, internal-external marketing, and human resources management (Yen, Le & Tran, 2019).

Moreover, it appears that many companies are increasingly adopting electronic business and information technologies such as social networks, semantic web, embedded systems, the internet of things, virtualization technologies, and cloud computing given the current highly competitive and rapidly changing business environment (Khayer, Talukder, Bao & Hossain, 2020). Digital technologies which are also known as Industry 4.0 technologies refer to social media, business analytics, the internet of things, big data, developed manufacturing, 3D printing, cloud computing, cyber solutions, high-performance computing, virtual and augmented reality (VR & AR), artificial intelligence (Aloini, Latronico, & Pellegrini, 2021; Popkova, De Bernardi, Tyurina & Sergi, 2022). These have now penetrated virtually every private and public sector institution and especially how to manage large loads of data (Aloini, Latronico & Pellegrini, 2021; Lee & Trimi, 2021). The Organization of Economic Co-operation and Development (OECD, 2017) stated that digital technologies provide businesses with new opportunities, including reducing significant barriers to e-commerce entry and inclusion in global value chains (e.g., Skype, Dropbox, Google, PayPal, Linked in, Amazon, etc.). In the late 1940s, definitions of SMEs started to appear due to the advent of government policies, new industries and markets, and they now shape many countries' economic, cultural, and social practices (Mashal, 2018). SMEs play a crucial role in the output, supporting large-scale manufacturing firms and creating regional and national job opportunities (Cerchione & Esposito, 2017; Abed, 2020; World Bank, 2021). Most companies worldwide are in fact SMEs and significant contributors to job growth and economic progress, particularly in developing countries.

According to the World Bank (2021), SMEs account for about 90% of companies and more than 50% of the world's employment, and in developing economies, SMEs contribute up to 40% of the national income. SMEs are significant to any country's economic growth because they are scalable, imaginative, and income-generating when things are going well for them (Taylor, 2019). However, access to finance is a major constraint for SMEs and their success in emerging markets and developing countries (World Bank, 2021). SMEs suffer from a shortage of financial capital, information systems and expert knowledge management (Casidy, Nyadzayo & Mohan, 2020). According to recent World Bank (2021) estimates, 600 million jobs will be required by 2030 to accommodate the world's rising workforce, making SME growth a top priority for many governments worldwide. However, the digitalization phenomenon is still under-researched in SMEs (Li, Su, Zhang & Mao, 2018), and the flood of research on digitization is mainly based on broader organizational contexts (Eller, Alford, Kallmünzer & Peters, 2020). Researchers studying technological change and technology entrepreneurship argue that dynamic capabilities and innovation speed are essential for gaining a competitive advantage and improving company performance (Prashantham & Floyd, 2012; Markovich, Efrat & Raban, 2021).

The Middle East has undergone a spectacular digital revolution in the last decade, with citizens, governments and business organizations using online platforms more than ever before. Companies in the Middle East are improving their ability to investigate and identify available online resources to invest in and succeed. As a result, the number of successful start-up businesses in the Arab World is increasing rapidly. Jordan is an Arab country with limited natural resources and the mining industry has only had a minor impact on the economy. Jordanian small business has been getting more attention from customers and the government alike (Al-Shamaileh, Saatci & Eyamba, 2020). Technology firms, SMEs and the Jordanian government are working together to develop a mature system (Adaileh & Alshawawreh, 2021). However, because Jordan has few natural resources, early investments have focused on technology and infrastructure, enabling increasing innovation and collaboration across industries (Lukonga & Joshi, 2020). The World Economic Forum has selected 100 start-ups in the Arab world that are transforming the Middle East region and especially in technology uptakes (World Economic Forum, 2019).

Prior research has looked at technology adoption in developed countries (Balta-Ozkan, Davidson, Bicket, & Whitmarsh, 2013a; Haque, Chin, & Debnath, 2013; Komninos, Pallot, &

Schaffers, 2013; Alsheddi, Sharma & Talukder, 2020; Thabit, Aissa & Jasim, 2021) but not so much in the Middle East, given that modern technology has yet to penetrate societies as much as it has in the Western world. Furthermore, there has been only a few studies conducted in Jordan identifying the determinants that provide a deeper understanding of digital technologies in the SMEs (Balta-Ozkan, Davidson, Bicket, & Whitmarsh, 2013b; Alsheddi, Sharma & Talukder, 2020; Ahmad, Jameel & Raewf, 2021; Lutfi, 2022; Alraja, Imran, Khashab, & Shah, 2022). This study fills that gap in our knowledge. In Jordan's increasingly free market economy, SMEs account for around 98% of all enterprises. Two-thirds have fewer than 19 staff members but still account for half of the country's private sector jobs (Jordan Times, 2019). According to the Jordanian Enterprise Development Corporation (JEDCO, 2021), the main problems regarding SMEs are access to new markets, lack of skilled workers and business planning, high competition from imported goods, obtaining finance or loans and lack of new technologies. The OCED (2017) reported that it is essential to encourage digital technologies in SMEs because they can resolve some of the conventional barriers to digital technology investment. However, despite the significant role that digital technologies play in day-to-day activities, there needs to be more empirical studies on identifying the determinants for adopting and using digital technologies in Jordan.

This study examines the utilization of artificial intelligence in small and medium-sized enterprises (SMEs) in Jordan, as measuring overall digital technology usage comprehensively is difficult (Warschauer, 2003; Warschauer & Matuchniak, 2010; van Dijk, 2012; Ragnedda, 2019). Despite being relatively new in small businesses, SMEs in Jordan are eager to use AI to remain competitive in the technology-driven era of globalization. It is widely believed that AI will play a crucial role in shaping the future of the economy (Parente, Silva, Junior, & Uhlmann, 2022). The COVID-19 pandemic has further accelerated the adoption of AI in SMEs as it enables businesses to maintain social distancing, carry out tasks remotely, and enhance customer service (Kumar & Kalse, 2021). SMEs in developing countries like Jordan are still exploring and experimenting with various forms of technology (Kumar & Ayedee, 2021). However, these businesses face several challenges such as poor information systems, lack of usage, and usability (Lutf, 2022). To remain competitive, governments and various business sectors must embrace digital technologies rapidly (Matikiti-Manyevere & Rambe, 2022). SMEs' utilization of digital technologies has been extensively studied, many SMEs in developing countries remain unaware of the benefits of these technologies (Matikiti-Manyevere & Rambe, 2022).

This research aims to address the knowledge gap regarding Jordanian SMEs' acceptance of digital technologies, specifically focusing on artificial intelligence (AI), which is considered one of the most crucial technologies for the future globally (Ulrich & Frank, 2021). The research will investigate the determinants of technological, organizational, political-environmental, and socio-cultural factors that affect Jordanian SMEs' acceptance of digital technologies. Additionally, socio-cultural determinants such as peer support and social networks will be considered, and religious beliefs will be measured for their impact on AI usage in SMEs. It is essential to approach the relationship between religious beliefs and digital technology usage respectfully and sensitively, considering ethical and moral considerations such as human values, privacy, and dignity. The research will also examine the impact of demographic variables on this issue. Identifying these determinants is crucial for SMEs to create a business environment that fosters the proper use of digital technologies, enabling them to predict how these technologies may affect their performance. This study will present a new theoretical framework applied to an empirical study and develop an advanced research model. The research will consider the strengths and limitations of previous technology acceptance models/theories by incorporating new themes. The study's combination of variables and testing will cover a wide variety of determinants, reflecting a fresh approach to studying SMEs and digital technologies. In this way, SME owners and managers in Jordan will understand the benchmark strategies to motivate their implementation of digital technology adoption and customize their operations to remain competitive in their relevant industry.

1.2 Motivation for this research

Globalization’s great expansion in the last three decades has forced SMEs to adopt digital technologies so that they can to some extent compete with large corporations. New digital technologies enhance performance and productivity in the modern era where the world is much more interconnected economically (Turaev & Ganiev, 2021). SMEs now rely on essential technologies that will lead to further technological adoption in new markets, but it is a slow process (Turaev & Ganiev, 2021). Scholarly studies on digitalization offer much-needed clarification but they have primarily been done in large-company contexts (Eller, Alford, Kallmünzer & Peters, 2020). SMEs in developing nations are still finding their feet and experimenting with various forms of technology (Kumar & Ayedee, 2021).

Digital technologies are a primary challenge for policymakers and SME administrators in many parts of the world (Morgan-Thomas, 2016). As stated by Adaileh and Alshawawreh (2021), Jordan's government established the REACH 2025 Vision in 2016, a strategy taking substantial steps in changing the economy to very digital one by 2025. REACH 2025 is critical for enabling individuals, industries, and businesses to adopt modern solutions and establish a solid foundation for commerce (Adaileh & Alshawawreh, 2021; Benhayoun, Ayala & Le Dain, 2021). SMEs tend to be more open to market changes and make more rapid decisions about how they want to transform their business model (Ching & Ghobakhloo, 2019). This is much more difficult for larger organizations to do (Beliaeva, Ferasso, Kraus & Damke, 2020). SMEs' embrace of technology can assist them in resolving challenges that arose during COVID-19, such as e-commerce, social media, and a variety of other online platforms (Kumar & Ayedee, 2021). Primary victims of the COVID-19 outbreak were the SMEs, particularly in developing countries. Because of the limited use of digital technologies and the need to be competitive in the commercial world, governments and business sectors must adopt and use these rapidly digital technologies (Matikiti-Manyevere & Rambe, 2022).

The lack of digital technologies has been a general concern among SMEs, including the paucity of knowledge and skills to apply them (Kilimis, Zou, Lehmann & Berger, 2019). Ferreira, Fernandes, and Ferreira (2019) argued that when we evaluate the impact of digital technology on a firm's performance, it remains a largely unexplored topic. Maroufkhani, Tseng, Iranmanesh, Ismail and Khalid (2020) noted the lack of digital technology-based empirical studies on SMEs' performance (see also Raut, Mangla, Narwane, Gardas, Priyadarshinee & Narkhede, 2019). Li, Su, Zhang and Mao (2018) found that SME digital transformation is an under-researched phenomenon. Verhoef and Bijmolt (2019) suggested the lack of empirical research on the relationship between the various stages of digital transformation and performance. The acceptance of digital technology and understanding its capabilities and improving SME performance still remain much unknown (Bi, Davison & Smyrnios, 2019).

Jordanian SMEs are still struggling to grow and thrive, cannot access finance and resources, and lack innovation (Mashal, 2018). Only a few studies have been applied in the Middle East region (particularly in Jordan) with reference to digital technologies. During November 2020, the Digital Cooperation Organization (DCO) in the Middle East was formally launched by representatives of Saudi Arabia, Jordan, Bahrain, Kuwait, and Pakistan, to advance digital transformation and grow the combined size of its members' digital economy to one trillion USD in the next 3-5 years (Access Partnership, 2021). The combination of variables and the testing of a wide range of determinants in this study represent a novel approach to understanding digital technologies' adoption in Jordanian SMEs. A vital element of this study will be the in-depth analysis of the technological, organizational, political-environmental, and socio-cultural contexts that affect how digital technologies are received in the SMEs.

1.2 Objectives for this research

Primary Objective

This study's primary objective is to identify the determinants affecting the adoption and use of digital technologies in Jordanian SMEs. It will help their decision-makers make the best calls concerning digital technologies to choose.

Specific Objectives

The following specific research objectives are articulated to find out what are the perceptions of digital technologies in Jordan SMEs:

1. Investigate the impact of the critical technological, organizational, political-environmental, and socio-cultural determinants on SMEs' perceptions of digital technologies.
2. Investigate the impact of demographic characteristics on SMEs' perceptions of digital technologies.
3. Investigate the impact of SMEs' perceptions of usage of digital technologies.
4. Investigate the expected benefits to Jordanian SMEs from implementing digital technologies.

1.4 Research Questions

The main research question of this study is:

What drives the adoption of digital technologies in Jordanian SMEs and their impact as perceived by owners/managers?

The specific research questions of this study are as follows:

1. What is the impact of technological, organizational, political-environmental, and socio-cultural determinants on SMEs' perceptions of digital technologies?
2. What is the impact of demographic characteristics on SMEs' perceptions of digital technologies?
3. What is the impact of SMEs' perceptions of digital technologies on usage level?
4. What are the expected benefits to Jordanian SMEs from usage and adoption of digital technologies?

1.5 Study's Rationale

The rationale for this research is the lack of extant literature on digital technologies adoption in the Middle East countries and especially Jordan. It explores various determinants of how digital technologies are embraced, so this study will establish a new paradigm and expand on what previous studies have done. Furthermore, the study results will contribute to our existing knowledge of what influences the acceptance of digital technologies in Jordan's SMEs. The research would not only help them understand the determinants and digital technologies adoption, but also other firms in Jordan to understand what improvements are required in terms of policies and strategies to enhance efficiency, productivity, growth, profitability, customer satisfaction, better sales, etc.

1.6 Significance of the Research

The study's intrinsic significance is its importance to the SME sector because these kinds of businesses play a key role in the economy and such as that of Jordan. This research will make a significant contribution in terms of understanding: firstly, what are the main determinants influencing the adoption of digital technologies in the Jordanian SMEs; and, secondly, how digital technologies can benefit these SMEs in terms of market share, customer satisfaction and sales, productivity, profitability, growth, etc. The aim of this research is to create a new and integrated model that is based on technology theories and models adoption and combines several variables. There are significant implications from the managerial viewpoint, as the study will enable SMEs owners/managers to understand what digital technology adoption will mean to them. The chief inference is that they can make good decisions based on digital technologies for the purpose of consolidating business needs and efficiency.

SMEs in developing nations such as those in the Middle East region generally do not yet fully understand digital technologies and why they are important (Dienes & Schneck, 2017; Abeh, Talib & Amoako, 2021; Lutf, 2022: Icks, Schröder, Brink). Further research is suggested to explore in-depth the features of digital technology adoption determinants in developing countries such as Jordan. A framework is required to explain the problems and challenges facing Jordanian SMEs when they are introduced to digital systems. This study is significant for the Jordanian economy and the findings will inform Jordan's policymakers in the government and industry on what digital technologies need to be implemented and in which industries. Digital technologies are widely used and are increasingly moving to become the key cornerstone of socio-economic life in many countries. They are opening prospects and new possibilities for businesses at the international level. This study will be of great interest to Jordan's SME customers, suppliers, and business partners. Government departments should define legislative and regulatory policies governing digital technologies.

1.7 Uniqueness of the Study/ Newness of the study

The findings of this research will add new knowledge to the topic being investigated. First, this study provides some new directions in deepening and broadening our understanding of what drives the adoption of digital technology in the Small and Medium-sized Enterprises context.

For instance, no previous research has used such a comprehensive model as this study did in terms of examining numerous issues under the broad categories of technological, social, political and environmental determinants. Furthermore, this research has combined these drivers to establish the perceptions and usage behaviors of digital technology in the SME context. Second, no prior research addressed the gap that exists in the literature concerning the impact of socio-cultural contexts including religious beliefs on digital technology adoption. This research suggests the growing importance of the socialization and value aspects in technology adoption in the SME sector. Third, very limited prior research has used perceived outcome variables in their investigations. Most research including the theoretical frameworks and models such as TAM, TRA, TOE, TBP, DOI or UTAUT used until levels of adoption and/or usage. No research took the further step to find what will happen regarding the performance of a business once technology is implemented. This research uses a large number of outcome/performance impact variables to assess the impact of the adoption of digital technologies in Jordanian SMEs' performance. These factors are expected to prompt further studies on the adoption behaviors of digital technologies throughout the changing Middle East and beyond.

1.7 Contribution of this Research

This research is one of the first systematic investigations on the adoption of digital technologies in SMEs in Jordan. Thus, the findings will contribute to the literature theoretically in terms of generating new insights as to whether or not the usage of digital technologies originating from developed industrialized economies has similar characteristics in Jordan's SMEs. Specifically, the findings could provide additional empirical evidence on the role of determinants in adopting digital technologies in SMEs. This study will makes important theoretical and practical contributions to the topic. They are explained in more detail below.

Theoretical Contributions

The study makes several theoretical contributions, and these are illustrated in more detail here.

Developing a model that incorporates technology adoption issues into a coherent model

This study creates a theoretical construct that integrates technological, organizational, political-environmental and socio-cultural contexts into one coherent model. This study's combination of variables goes beyond previous research to bring together all the relevant determinants that may affect the perceptions and use of digital technologies in the workplace. The study combines multiple sets of variables found in technology adoption-related literature into a single study context. The study examines relationships between digital technology adoption and the drivers that affect and determine this adoption by small and medium-sized enterprises.

Filling the knowledge gap

Although many studies have been conducted on technology adoption in developed countries, only a few were done in developing countries and the Middle East is no different. This study will fill the research gaps and contribute to knowledge on the drivers of adoption of digital technologies in SMEs and their impact on organizational performance. The study uses socio-cultural determinants such as religious beliefs which have not been explored beforehand. In the Middle East, socio-cultural aspects such as religious beliefs greatly shape or guide employees' daily activities.

Extending the theoretical model by adding outcome variables to the existing model

The existing technology adoption-related theories did not go beyond the adoption and usage levels in their models. One of the limitations of those theories that they did not look at the impact on organizational performance when they adopt a new technology. For example, the theory of reasoned action (TRA), theory of planned behavior (TPB), the technology acceptance model (TAM), the unified theory of acceptance and use of technology (UTAUT), DeLone and McLean information systems success model (IS success model), and technology-organization-environment (TOE) framework do not have any outcome variables. This study extends the technology adoption model (TAM) by adding outcome variables. This study explores the variables and their outcomes for digital technologies adoption which has not been done previously. The study will explore key variables identified in the literature, checked if they are relevant and analyze if there are any discrepancies between the variables, leading to a better awareness and a more comprehensive theoretical foundation.

Practical Contributions

The study makes several practical contributions as follows:

Contribution to the Jordanian government

Given the relative importance of SMEs in many economies, governments have taken steps to guarantee this sector is not left behind as the digital era expands well into the future. Globalization and technological change have in the last few decades ushered in a shift in the way businesses and governments function in the Middle East and beyond. These countries are making serious efforts to construct technological environments with superior capabilities to create the desired economic conditions. This research will be used as a guide for government officials. In Middle Eastern countries, it is helping them better grasp the key aspects that drive digital technology acceptability so that they can do business better with other countries. They will be able to design strategies for successfully using new systems if they have a better understanding of the major determinants. The study, if empirically verified, could aid in evaluating the impact of digital systems and providing direction on how political action might aid in the development of digital technology and its deployment.

Contribution to organizations in any sectors.

The adoption of digital technologies in SMEs in Jordan will promote management awareness, understanding and support for new ways of doing business domestically and internationally. It will make a difference by assisting both the government and SMEs in better understanding new technologies and the variables that influence how businesses operate. SMEs will be able to examine the suggested integrated model and assess the external and internal issues that influence the adoption process. SMEs owners and/or managers will be able to design new business strategies, procedures and policies to use digital technologies if they understand the critical determinants successfully.

Contributions to Management Personnel

The research will assist owners-managers and SMEs in developing policies when it comes to embracing digital technologies. This research will identify the essential determinants that influence digital technology adoption, and the findings enable government agencies and owners/managers to utilize the system successfully. Owners/managers interested in testing, understanding, and implementing digital technology in SMEs sectors will be assisted by the findings documented here. It will also help them respond more quickly to changes in their external environment and reduce risk and uncertainty, or at least identify what they are and how to work around them. Managers will be able to plan and prepare for digital technologies but also ensure that doing so allows for a smooth transfer of processes. Furthermore, this research may reduce issues related to cost, setting up, etc., of digital technologies in SMEs.

1.9 Structure of the Thesis

This thesis is structured into seven chapters, and they are summarized below:

Chapter One: Introduction: This chapter introduces the topic, informs the reader about the research problem, objectives, the questions to be asked, motivation to cover the research gaps, rationale, significance and uniqueness or newness of the study. The theoretical and practical contributions for the benefit of Jordanian SMEs are articulated. It also explains why the proposed research model is essential.

Chapter Two: Literature Review: The literature review includes a detailed evaluation of the literature concerning definitions and typologies of digital technologies, the benefits of digital technologies, the adoption process, digital technologies in Jordan, the concept of small and medium-sized enterprises (SMEs) and how they operate in Jordan. Comments on their digital technologies are also made in this chapter.

Chapter Three: Theoretical Framework: This chapter reviews theories and models within the technology adoption domain. This chapter outlines the existing theories and models that are relevant to this study. These including the theory of reasoned action (TRA), technology acceptance model (TAM), and Its Extensions, technology acceptance model 2 (TAM2), Diffusion of Innovations (DOI) theory, the unified theory of acceptance and use of technology (UTAUT), the TOE framework adopted models, electronic data interchange (EDI), De Lone and McLean's information systems success model, combined TAM and TPB, the motivation theory, the model of PC utilization, the social cognitive theory (SCT), technology readiness index (TRI), resource-based view (RBV), Knowledge-based view (KBV), institutional theory and adopted models and theories justification.

Chapter Four: Advanced Research Model and Hypotheses Development: Described here is the proposed model based on the outcomes of the literature review and especially the theoretical frameworks scholars suggested. This chapter outlines how the research model was devised for explaining digital technologies in Jordan using the four categories: organizational, technological, socio-cultural, and political-environmental contexts. The demographic characteristics consist of seven variables: gender, age, academic qualification(s), employment experience, industry classification, number of employees, and role in the business. Discussions on all variables are then provided and then the hypotheses are stated. Finally, the model outcomes, including SME performance and growth, productivity, profitability, market share, customer satisfaction, and improved sales, are explained.

Chapter Five: Research Method and Analytical Framework: The chapter explains the quantitative methodology and the answers acquired through the online survey. The chapter begins with a discussion of the research philosophy, design, quantitative analysis, sample population for the study, sampling size, measuring instruments used and the variables. Defined here are the constructs and measures of the study's variables, validity and reliability, and data collection procedures.

Chapter Six: Data Analysis and Discussion: This chapter implements a systematic analysis of data collected from owners/managers of SMEs in Jordan. The conceptual model tested statistically using data garnered from the online questionnaire survey. Subjected to analysis here are respondents' answers, followed by the variables' correlations. It then discusses the study's validity and reliability, along with the variables impacting digital technologies adoption, regression analyses, model assumptions, and hypotheses. The main findings, including an analysis of SMEs perceptions that support the proposed model are summarized. Exploratory factor analysis (EFA) validated the research model. The structural path model used SPSS to test the advance proposed model and the worthiness of the hypotheses.

Chapter Seven: Conclusion, Implications and Recommendations. This concluding chapter summarizes the key themes and findings on digital technologies in Jordan's SMEs. The conclusion will demonstrate how this study has built on and expanded previous research and added new knowledge to this subject, especially in terms of a broader theoretical understanding of technologies adoption. It also addresses the practical implications for owners, managers and other relevant staff working in the SMEs. The study's limitations and future research possibilities on this topic are stated.

Appendices. The last part of this thesis includes three appendices. The first appendix is the participant information form. The second appendix is the approval letter of the research ethics and integrity research committee from the University of Canberra. The third appendix is the survey questionnaire which was distributed to Jordanian SMEs in Amman.

1.10 Conclusion

This chapter has provided the relevant background information on the topic of digital technologies and described how they now function as an integral part of businesses. The chapter defined digital technologies based on what the literature has found. It also clarified the objectives of the research, which include an evaluation of what determines the adoption of digital technologies, what this means for organizational performance, and whether benefits arise from it. Highlighted here are the issues of research significance and rationale, theoretical and practical implications, and how a new comprehensive model will be devised. Finally, business managers, policymakers and other relevant practitioners will be able to make appropriate decisions about how to effectively employ digital technologies based on the conclusions drawn in this study. The proposed model will lead to a better understanding of digital technologies based on several sets of variables. The following chapter is concerned with a detailed literature review, and this entails examining the relevant research that has been published on digital technologies adoption.

CHAPTER TWO: LITERATURE REVIEW

2.1 Introduction

This chapter reviews the literature that has explored this topic, especially the work done on adopting digital technologies in small and medium-sized enterprises (SMEs) in the Hashemite Kingdom of Jordan (Jordan). Various definitions and benefits of digital technologies are offered here. It also discusses the typologies of digital technologies and the adoption process and the digital technologies in Jordan. This chapter explains the concept of small and medium-sized enterprises (SMEs) in Jordan. Then, it discusses the digital technologies and SMEs, and the last section discusses SMEs' performance.

2.2 Definitions of Digital Technologies

Digital technologies are hardware, software, systems and processes that use digital data or signals to achieve specific user-defined outcomes (Tulinayo, Ssentume & Najjuma, 2018). They are in effect the electronic and digital tools used to gather, store, and evaluate data/information (Fuentes, Tongson & Viejo, 2021). The concept of the fourth industrial revolution (Industry 4.0) is underpinned by the development of information and communication technologies (ICTs) and data storage (Nascimento, Alencastro, Quelhas, Caiado, Garza-Reyes, Rocha-Lona & Tortorella, 2018). Digital technologies constitute a broad term that refers to an organization's use of information systems (IS), Information, Communication Technologies (ICTs), and Information Technology (IT) to create a novel product, method, or business model (Ramdani, Kawalek & Kayumova, 2021).

Digitalization means using digital technologies to change an organization's business model in a way that offers new revenue and value creation opportunities (Westerlund, 2020). Uses of digital technologies include remote meeting facilitation (e.g., Skype, Google meetings, Zoom meetings), communications like email and social media buying and selling online, digital televisions, eBooks, smartphones, drones and guided missiles, robotics and banking and finances (Goodman, 2022). Garzoni, De Turi, Secundo and Del Vecchio (2020) described digital technologies as an iterative process consisting of gradual and disruptive changes

(Barann, Hermann, Cordes, Chasin & Becker, 2019). It can include automated business processes (Lombardi, 2019) and its implementation involves modifying the business model by digital technology to drive technical progress (Frank, Mendes, Ayala & Ghezzi, 2019). There are various definitions of digital technologies in the literature. According to Ibrahim (2013), digital technologies as "Innovations" assist construction industry management teams to complete building projects based their procurement strategies. It is an essential enabler of circular economy business models (Ranta, Aarikka-Stenroos & Väisänen, 2021).

Digital technologies are a computer-driven innovation that shapes the economy and society (Chawla & Joshi, 2020). The study by Rachinger, Rauter, Müller, Vorraber and Schirgi (2018) postulated that digitalization describes digital technology's use to modify a business model/services or products. As an example, Digital Multi-Sided Platforms (MSPs) can generate value by facilitating transactions in international or global markets between buyers and sellers (Stallkamp & Schotter, 2019). Their average time for international penetration has reduced from several years to a few weeks (Shaheer & Li, 2020) because more digital technologies are available globally from the beginning via digital MSPs. The conversion to a digital form of handwritten or typewritten text is an example of digital technologies such as transferring music from a VHS tape from an LP or video. However, it continues to develop and create new outcomes for the organizational climate in any business. Digitalization strongly suggests a variety of different functions and business models (Crittenden & Peterson, 2019).

Digital technologies now constitute the fourth industrial revolution (Industry 4.0) technologies. This phenomenon was first described in 2011 as a suggestion for implementing a new paradigm in Germany, based on high-tech policies and the government's economic strategy (Mosconi, 2015; Schwab, 2016). The Industry 4.0 concept centred on the principles and technologies that involve cyber-physical networks, the Internet of Things (IoT) and the Internet of Services (IoS) (Von Solms, Langerman & Marnewick, 2021). The main factor that characterizes Industry 4.0 is the shift in production processes that enable information and communication technology (ICT), the internet of things (IoT), and machines to be incorporated into the cyber-physical system (CPS) (Dalenogare, Benitez, Ayala & Frank, 2018). The four kinds of digital technologies are known as the foundations of Industry 4.0, and they consist of the internet of things (IoT), internet of service (IoS), smart factory (SF) and cyber-physical system (CPS) (Roblek, Meško & Krapež, 2016).

Digital technologies are described as the fundamental transformation of industry according to the i-SCOOP.EU online guide to digital business transformation, processes, competencies, and templates for completely exploiting operational activities and organizational activities, the shifts, and possibilities of a synthesis of new technologies, and their acceleration effect systematically and prioritized through society and with future improvements in mind (Pihir, Tomičić-Pupek & Tomičić Furjan, 2019). The concept of digital technologies oneself is not consistently defined so there is a lack of agreement here (Denner, Püschel & Röglinger, 2018). Nevertheless, the previous definitions and arguments are realistic and rational and reveal some consistency, where variations can depend on the level of technology adoption between developed and developing countries.

Digital technologies may be defined as tools or something akin to a new, substantially enhanced concept, system or technology that can be implemented by any organization or individual to generate added value and enhance the efficiency of activities. Hence, digital technologies add value to firms, and they will only be regarded as digital technologies when they are implemented (Fuentes, Tongson & Viejo, 2021). The rapid growth in adopting these digital technologies worldwide motivates many business leaders to consider how to best position their companies to benefit from this trend (Ortiz-de-Mandojana & Bansal, 2015). This is very relevant to how SMEs organize their daily activities. Much effort is required in all departments, units, etc., to assimilate or integrate digital technology, such as employees' participation and training so that they can execute the financial and managerial duties through the accepted technical infrastructure. The definitions in this section indicate that digital technologies have many standard or generalizable features, and they shape the business positively. The following section discusses typologies of digital technologies.

2.3 Types of Digital Technologies

Today's world is characterized by significant social, economic, and technological changes and these are very widespread. The influence of digitalization on our lives and business is all-consuming. It plays a role in progressing or advancing the economy, improving business outcomes, creating competition, creating higher quality, and improving standards and productivity. Today, many businesses are confronted with substantial problems in terms of long-term viability and technical developments, and to solve difficulties, models and tools have been devised (Díaz-Piloneta, Ortega-Fernández, Morán-Palacios & Rodríguez-Montequín, 2021). Researchers have typically classified digital technologies into various forms that are especially important for industrial and social networks, with great ramifications at the individual level. Several studies noted three distinct but linked parts, namely digital artifacts, digital platforms, and digital infrastructure (e.g., Rippaa & Secundo, 2019; Elia, Margherita & Passiante, 2020; Popović-Pantić, Semenenko & Vasilić, 2020). The typologies of digital technologies are explained in more detail below.

2.3.1 Digital Artifact

The term 'digital artifact' is related to a feature, application, or aspects of media content that constitute a new product (or service) and provides the end-user with a particular functionality or value (Kallinikos, Aaltonen & Marton, 2013). It is possible to transfer physical product "artifacts" such as books into digital form so that they become "digital artifacts" (Gabrielsson, Fraccastoro, Ojala & Rollins, 2021). Digital artifacts are distinct from physical ones in terms of editability, interactivity, programmability, and how they are transmitted across various sources from physical entities and other cultural documents, e.g., paper-based archives, tape recordings to digital artifacts (Kallinikos, Aaltonen & Marton, 2013). Digital artifacts are linked to five categories of digital technologies: digital storytelling, digital business portfolio, virtual and augmented immersive reality technologies virtual, conversational system and blockchain (Rippaa & Secundo, 2019). Blockchain has become an innovative and promising technology. Its proponents argue that it has nearly limitless uses in various industries, including banking, energy production, the internet of things, health, and media (Berdik, Otoum, Schmidt, Porter & Jararweh, 2021). It can take over any domain because of its security features (Chen, Jiao, Han, Shen, Du, Ye & Yu, 2020; Rippaa & Secundo, 2019).

2.3.2 Digital platform

Digital platforms refer to shared, standard services and modular architecture, including digital artifacts that host complementary offerings (Parker, Van Alstyne & Choudary, 2016). It can be described as a software-based platform created by a system's extensible codebase that provides the core functionality shared by modules and interfaces it interacts with, such as iPhone apps

(Tiwana, 2014). Digital platforms are typically designed to organize information technology capabilities into structures so that the software can address a family of generic requirements that meet multiple, heterogeneous, and growing user groups' needs (Hanseth & Lyytinen, 2010). Platform technologies and business models are used by the fastest-growing companies, such as Amazon, Netflix, Uber, and by 2016, over 170 platform firms globally were valued at $1 billion or more (Kiesling, 2021). The platforms for operating systems such as Android and iOS have been centred on the mobile telecommunication industries. Payment facilities such as PayPal, Apple Pay, and Square are disrupting the banking industry and sharing economy such as Uber, Airbnb and TaskRabbit (De Reuver, Sørensen & Basole, 2018). Rippaa and Secundo (2019) claimed that digital platforms are intelligent applications, e.g., Mesh app and service architecture (MASA), Big data-learning analytics, cloud computing and social media. Furthermore, intelligent apps are virtual customer assistants and competent advisors. MASA for mobile, website, desktop and IoT applications connect to a vast network of back-end services to construct what users perceive as an "application", permitting users to find the best solution for specific endpoints.

Cloud computing is now ubiquitous in the private and public sectors because it links people globally across many networks. It provides a creative and innovative business model for access to virtualized and distributed resources such as networks, applications, storage, servers, and services that are ubiquitous, convenient, and on-demand (Khayer, Talukder, Bao & Hossain, 2020; Asghari & Navimipour, 2018). The use of cloud computing has changed current business structures, through the processes of digitization and automation in manufacturing and services, providing businesses with more agility, versatility, and efficiency (Ooi, Hew & Lin, 2018). Computer-mediated systems that enable the sharing of information, ideas, career interests, and other kinds of expression through virtual communities and networks are known as social media, for instance Facebook, Linkedin, and Twitter (Rippaa & Secundo, 2019). Wu (2016) demonstrates that social media's adoption and marketing improves organizational creativity and learning performance. Businesses will benefit from new information technology such as social media both in terms of products, services, and market share (Turaev & Ganiev, 2021).

2.3.3 Digital infrastructure

Digital infrastructure is characterized as the tools and digital technology systems that provide communication, collaboration, and computing (Nambisan, 2017). Melville and Kohli (2021) defined digital infrastructure as shared, heterogeneous, unbounded open, socio-technical systems involving information technologies, processes, communities, and associated capabilities. Rippaa and Secundo (2019) stated that digital infrastructure, including artificial intelligence (AI) and advanced machine learning, Intelligent things, additive manufacturing /3D Printing, Internet of things (IoT), drones, etc. Intelligent things, including physical devices and apps and services (deep learning, neural networks, natural-language processing), are created by applying artificial intelligence (AI) and advanced machine learning (Zolkin, Burda, Avdeev & Fakhertdinova, 2021). 3D printing refers to processes used to create a three-dimensional object (Rippaa & Secundo, 2019). Additive manufacturing has revolutionized traditional manufacturing, where the material is deposited or inserted rather than cut or subtracted to get the desired component or part (Marzi, Zollo, Boccardi & Ciappei, 2018). New machines result in rapid deposition technology and material breakthroughs, rapidly elevating additive manufacturing technology from the prototype stage to mainstream production.

The Internet of things (IoT) will cause current business processes to shift drastically and reduce both losses and waste so that new intelligent objects are created, in conjunction with other digital technologies and domain-dependent applications, e.g., smart transportation, smart cities, intelligent plants (Kilimis, Zou, Lehmann & Berger, 2019). Furthermore, the industrial internet of things (IIoT) is making significant progress in revolutionizing the manufacturing market. It gives the production system an efficient and flexible exchange of information between intelligent entities and optimizes the value chain (Vaidya, Ambad & Bhosle, 2018). According to Kilimis, Zou, Lehmann and Berger (2019), industrial internet of things (IIoT) applications include predictive maintenance, product improvement, energy savings, employees' better productivity and delivery of services (see also Ng & Wakenshaw, 2017; Boyes, Hallaq, Cunningham & Watson, 2018; Vaidya, Ambad & Bhosle, 2018).

Digitalization's technological core requires functional processes, such as design, analysis and testing, scheduling, manufacturing, quality, maintenance, equipment, machines and robots, tools, and business tools—connected applications such as enterprise resource planning (ERP) and product lifecycle management (PLM) that make SMEs fulfil their business aspirations (Dutta, Kumar, Sindhwani & Singh, 2020). The digital simulation aims to make it possible for designers and engineers to rapidly review and test—design alternatives with live data to promote successful innovation in both these fields. Wang, Wan and Zhang (2016) postulated that there is another type of digital technology, and this known as the Smart Factory (SF), which is related to the refinement of IoT or IoS. This study is concerned with the determinants of adopting digital technologies in Jordanian SMEs and how it shapes their performance, manufacture and/or sales of products. The right information about a digital technology helps SMEs understand how to develop their goods, products and services, and reduce their costs or overheads. The following section is concerned with the benefits of adopting digital technologies in SMEs. The standard digital technology types are summarized in Table 1.

Table 1: Digital Technology Types

Digital technologies	**Definitions and Sources**
1. Building information modelling (BIM)	BIM: A digital representation of a structure or a building facility of physical and functional features (e.g., Ashworth & Perera, 2018; Sacks et al., 2018; Gu & London, 2010; Woodhead et al., 2018; Tang et al., 2019; Bosch-Sijtsema, Claeson-Jonsson, Johansson & Roupe, 2021; Luo, Zhang, Wang & Wang, 2021).
2. Sensors/Internet of things (IoT)	It is a device that collects data or signals. Sensors, such as light, temperature, humidity, CO2, and others, allow us to acquire data from the physical world (e.g., Ashworth & Perera, 2018; Skibniewski, 2014). In AEC, IoT is frequently associated with connected and automated sensors (Chen et al., 2020; Woodhead et al., 2018; Tang et al., 2019; Bosch-Sijtsema, Claeson-Jonsson, Johansson & Roupe, 2021). Internet of things (IoT) means electronics, software, sensors, actuators, mobile devices that communicate and cooperate by exchanging information through networking to achieve a shared operating scenario (Gubbi et al., 2013; Rippaa and Secundo, 2019; Kyriakopoulos et al., 2020; Zolkin, Burda, Avdeev & Fakhertdinova, 2021).
3. Cloud computing	Cloud computing related to calculations, analyses, and other cloud-based activities (not storage) (Woodhead et al., 2018; Zhang & Issa, 2012). It is a sort of Internet-based computing that supply on-demand computers and other devices with shared computer processing resources and data (Rippaa & Secundo, 2019). It is a blueprint for universal, on-demand access to a shared pool of configurable computing resources (Ooi et al., 2018; Rippaa & Secundo, 2019; Bosch-Sijtsema, Claeson-Jonsson, Johansson & Roupe, 2021).

4. Virtual Reality (VR), Augmented Reality (AR) or Mixed Reality MR	Virtual Reality (VR), Augmented Reality (AR) or Mixed Reality – many sorts of computer-generated interactive experiences that depict and visualize a natural environment virtually (e.g., head-mounted displays). Getuli et al., 2020; Johansson et al., 2015; McMeel & Gonzalez, 2019; Lin et al., 2020; Zaher et al., 2018; Syberfeldt et al., 2014; Dutta et al., 2020; Bosch-Sijtsema, Claeson-Jonsson, Johansson & Roupe, 2021).
5. 3D scanning	A device that can read a three-dimensional object's shape and preserve it as points/3 D coordinates (Guo et al., 2020; Skibniewski, 2014; Bosch-Sijtsema, Claeson-Jonsson, Johansson & Roupe, 2021).
6. Drones	Unmanned aircraft operated by a computer that may be used for a variety of tasks, including cinematography, photography, 3D scanning, and other sensors (Albeaino et al., 2019; Zhou & Gheisari, 2018; (Bosch-Sijtsema, Claeson-Jonsson, Johansson, & Roupe, 2021).
7. Robots and automation	Robotization and automation refer to the use of a computer or machine to undertake manual, repetitive work instead of humans (Adan et al., 2020; Bock & Linner, 2015; Skibniewski, 2014), such as a brick-laying machine, automatically generated design, and automated quality control (Bosch-Sijtsema, Claeson-Jonsson, Johansson & Roupe, 2021). Autonomous robots execute actions based on their own decisions. An Autonomous robot can be programmed to respond in a particular manner, and based on its environment and surrounding operational dynamics, it makes decisions to identify, comprehend and then actuate a motor-controlled maneuver within that environment (Qin et al., 2016; Dutta et al., 2020).
8. Additive manufacturing AM- 3D printing	AM The machine produces three-dimensional material objects after drawings made in a computer (Balasubramanian et al., 2017; Marchment & Sanjayan, 2020). It is referred to processes used to construct a three-dimensional object. Under computer control, layers of material are shaped to construct almost any shape or geometry of an object generated using digital model data from a 3D model or another electronic data source (Rippaa & Secundo, 2019). Additive manufacturing, also known as 3D printing, combines materials layer by layer, similar to machining (Ivanov, Dolgui & Sokolov, 2019; Bosch-Sijtsema, Claeson-Jonsson, Johansson & Roupe, 2021).
9. Self-driving vehicles	Self-driving cars, lawnmowers, vacuum cleaners, and other vehicles are controlled and operated automatically by the vehicle sensing its navigating without human input and surroundings (Bosch-Sijtsema, Claeson-Jonsson, Johansson & Roupe, 2021).
10. Machine learning ML/ Artificial Intelligence AI	Sourdin (2018) defines Artificial Intelligence as "the theory and development of computer systems capable of doing activities that ordinarily require human intelligence." (Bosch-Sijtsema, Claeson-Jonsson, Johansson & Roupe, 2021). Machine learning (ML) is studying how computers can "learn" from data without having to be

	programmed to do so. AI is a system of intelligent behavior that observes its surroundings and acts to achieve a predetermined goal (e.g., Ashworth & Perera, 2018; Darko et al., 2020; Nath et al., 2020; Woodhead et al., 2018), Automated construction site safety and risk management, for example, automated production planning; and predict and monitor facility management data, to name a few examples.
11. Digital twin	It is an exact digital picture or image of a machine, building, construction, or city in the form of software (Boje et al., 2020; Woodhead et al., 2018), e.g., virtual Singapore, a digital copy of a machine, building, construction, or city (Boje et al., 2020; Woodhead et al., 2018; Bosch-Sijtsema, Claeson-Jonsson, Johansson & Roupe, 2021).
12. Cyber-physical systems (CPS)	Integrated systems with computation, networking, and physical process capabilities, in which highly integrated physical and digital components enable interaction between geographically and temporally disparate systems and adaptability to changing circumstances (Kilimis, Zou, Lehmann & Berger, 2019; Rudtsch et al., 2014; Kang et al., 2016; Thoben et al., 2017; Dutta et al., 2020).
13. Digital Storytelling	Meaning a platform for interactive multimedia storytelling, such as pictures, audio, video, and animation to present information on a given subject, these stories put together a mixture of digital graphics, video, audio narration, text, and music (Rippaa & Secundo, 2019; Robin, 2006). New media technologies, such as hypertexts and multimedia resources, are blended into the narration, introducing new concepts, and encouraging participation, resulting in new media cultures (Podara, Giomelakis, Nicolaou, Matsiola & Kotsakis, 2021).
14. A digital business portfolio	A digital business portfolio is a user-assembled and managed collection of electronic documentation, usually on the Web. It is also known as an electronic, online portfolio, a digital portfolio, an e-portfolio, and e-folio (Zimmerman, 2014). These digital portfolios enable business students and professionals to critically evaluate their work, such as presentations and research articles (Rippaa & Secundo, 2019).
15. Conversational systems	Standard desktop computers and several computers, the system mesh move to cover the full spectrum of endpoints in which humans can communicate, such as chatbots and devices activated by microphones (Rippaa & Secundo, 2019). Conversational systems are expected to significantly impact human-computer interaction, according to both the research community and industry, and the CHI/IR/DM/RecSys communities have begun to investigate conversational recommendation Systems (Fu, Xian, Zhang & Zhang, 2021). Included here are both physical devices and mobile-based applications, which have emerged in recent years (Fu, Xian, Zhang & Zhang, 2021).
16. Blockchain	Blockchain is digital a distributed ledger in which bitcoin or other cryptocurrency transactions are registered chronologically and

	publicly through hashing and distributed algorithms; transactions on the blockchain are almost tamper-proof (Rippaa & Secundo, 2019; Berdik et al., 2021).
17. Intelligent applications perform	Perform some of a human assistant's duties, making daily activities more straightforward and more efficient (competent advisors, virtual customer assistant) (Rippaa & Secundo, 2019).
18. Mesh applications and service architecture (MASA)	Mobile applications, web apps, desktop apps and IoT apps attach to an extensive network of back-end services to build what users see as "software." The MASA helps users to provide a solution that is optimized. For instance, digital finance (e.g., Kickstarter), accessibility (e.g., Uber) and health care (e.g., PatientsLikeMe) innovations are all powered by digital platform logic (de Reuver et al., 2018; Rippaa & Secundo, 2019).
19. Big data	It can be characterized as large data volumes and large data variety. Applying algorithms to analyze data sets to derive functional and previously unknown patterns, relationships, and knowledge is referred to as big data analytics. It implements new techniques for extracting secret patterns from collecting raw data to make correct decisions, increase efficiency, generate information, and update innovations (Acharya et al., 2018; de Vasconcelos & Rocha, 2019; Yaqoob et al., 2016).
20. social media	Computer-mediated technologies encourage how people interact and share experiences and sharing through virtual communities and networks of knowledge, career interests, ideas, and other forms of speech. Facebook, Linked In, and Twitter are examples (de Reuver et al., 2018).
21. Intelligent things	Brilliant stuff refers to physical things beyond rigid programming models to utilize applied Artificial Intelligence and machine learning to produce advanced behaviors and communicate more naturally with people and their surrounding worlds, such as autonomous vehicles, drones, and intelligent appliances (Rippaa & Secundo (2019).
22. Industrial Internet of Things (IIoT)	(IIoT) to monitor, organize and manage the physical environment of products, equipment, factories, and infrastructure, it integrates the global reach of the internet with industrial capabilities in a way that has begun to influence traditional markets, value chains and business models (Dutta et al., 2020). Since the (IIoT) for industrial applications requires more excellent reliability and real-time data availability and therefore differs from the IoT for users, it is referred to as the (IIoT).
23. Big Data Analytics	Big Data's consensual concept narrates how we can exploit "data sets whose scale goes beyond the capacity of widely used instruments to process it in a reasonable time." Big Data is defined by three Vs, Gartner information technology research volume, velocity, and variety. The data is produced from an ever-expanding number of sources, channels, and sensors and in a wide variety of formats, so the need is to get the data processed fast to be sensitive as the events

	occur. Big Data growth is the result of rapid developments of social networking, advanced mobile technology, e-commerce websites, search engines, etc. (Gartner, 2018; Dutta et al., 2020; Surbakti et al., 2020).
24. System Integrating	An effective mechanism used in manufacturing organizations is integration. Three integration dimensions essentially constitute the industry 4.0 paradigm. System Integrating consist of from Dimension 1: Horizontal convergence in the network of value formation Inbound logistics for ordered raw materials or sub-assemblies, supplier strategies, manufacturing operations, outbound logistics, including warehouse strategies and dealer management, marketing and sales are essentially the horizontal value creation network. Dimension 2: Vertical Integration and Networked Manufacturing Systems A modern manufacturing plant is equipped with various machines. Dimension 3: End-to-end integration through product life cycle processes a product undergoes many design changes during its entire life cycle from conception to end-of-life (Dutta et al., 2020).
25. Digital simulation	Digital simulation has many functions linked to product development and manufacturing. Typical discrete manufacturing companies will target two broad development types: new product creation and enhancements to existing products. In both cases, the secret to successful innovation is improving the incumbent and reducing the risk of failure, which most certainly contributes to sales growth (Mourtzis et al., 2013; Thomke & Fujimoto, 2000).

2.4 Benefits of Adopting Digital Technologies

The global digital transformation market was estimated to be worth USD 594.5 billion in 2022, and this will rise to USD 1548.9 billion by 2027 at a Compound Annual Growth Rate (CAGR) of 21.1% during the forecast period (Market & Market, 2022). Furthermore, it has been predicted that the global digital transformation market was worth US$284.38 billion in 2019 and is forecast to rise at a 22.5% compound annual growth rate (CAGR) from 2020 to 2027 (Statista, 2022). The benefits of digital technologies in the Industry 4.0 context can provide a wide range of advantages and solve some issues. For example, information and communication technologies help SMEs gain access to external loans and credit facilities (Von Solms, Langerman & Marnewick, 2021; Agyekum, Reddy, Wallace & Wellalage, 2021). Digital technology's objective is to transform companies through the implementation of modern technology and the introduction of new business processes in order to develop new or enhance existing goods and services so that they sell well in the global market (Pihir, Tomičić-Pupek & Tomičić Furjan, 2019).

Thus, a rapidly shifting business environment had driven businesses to embrace the latest information technologies such as semantic web, embedded systems, virtualization technologies (VT), the Internet of Things (IoT), cloud computing and social networks (Naveed, Watanabe & Neittaanmäki, 2018; Khayer, Talukder, Bao & Hossain, 2020). Digital technologies can create new expectations and changes, but they also have the potential to disrupt old practices or pose a threat to businesses that believe their investment in innovation and expertise is excessive and are hence less willing to adapt to new trends (Bosch-Sijtsema, Claeson-Jonsson, Johansson & Roupe, 2021). Westerlund (2020) asserted the benefits of digital technology as ICT as follows: 1) reduced response time, costs of operations, transaction times, and dependency on physical documents; and 2) improved competitiveness, productivity, product or service quality, information sharing, multi-skilling, partnerships and collaborations, training, ease of access, marketing, and remote working. Organizations and society can benefit from digital technologies in their attempts to become more viable (Díaz-Piloneta, Ortega-Fernández, Morán-Palacios & Rodríguez-Montequín, 2021).

The recent COVID-19 crisis has been a significant threat to the global economy since late 2019 and that danger remains to this day. Digital transformation will help businesses overcome the challenges posed by social distancing, lockdowns, working from home, and other government or industry mandates. For example, in Jordan (as is happening elsewhere in the world) local restaurants have reinvented themselves and are concentrating on delivery services. The ability to employ new consumers' demands and a willingness to adopt technology to enhance products and services are common characteristics companies have, and they want to achieve success during these challenging times. Companies need to be receptive and attentive to resolve any crisis as COVID-19. Some developing countries like Jordan have encountered great difficulties for their firms resulting from a lack of a digital strategy, software, and the infrastructure to work from home. Another business barrier is ensuring employee efficiency, developing digital technologies, and enabling coordination across dispersed workforces. This is something that SMEs need to work on when it comes to new ways of dealing with financial and human capital (Tseng & Johnsen, 2011; Tarutė & Gatautis, 2014). According to Grand View Research (2022), despite the damage inflicted by COVID-19 on businesses, families, and communities, it has created opportunities. Since technology improves performance and productivity when used properly, the outbreak is allowing businesses to operate on their digital platforms. Digital transformation solutions will assist teams in learning to communicate, and businesses will understand that they can operate effectively without having employees in the workplace. This scenario is expected to drive the digital transformation market's progress (Grand View Research, 2022). Several aspects that impact businesses positively are documented in the following sections.

2.4.1 Digital technologies Improve Competitive

The rapid changes occurring in the Internet of things, big data and robotics, social media, smart mobile and cloud computing have fundamentally altered the competitive landscape, models, processes, and reshaping traditional corporate strategies (Elia, Margherita & Passiante, 2020; Zide & Jokonya, 2022). There is evidence that digital technologies appropriate for strategic adoption reasons can increase competitiveness, efficiency, and performance (Chan, Griffin, Lim, Zeng & Chiu, 2018). Digital technologies are used in nearly every industry worldwide to gain a competitive advantage (Trinugroho, Pamungkas, Wiwoho, Damayanti & Pramono, 2021). Companies have increased their investment in digitalization to keep up with what their competitors are doing. Rapid advances in cloud computing and the advent of cutting-edge technologies like artificial intelligence and the Internet of things (IoT) tools have made it possible for SMEs to adopt digital technologies (Grand View Research, 2022; Wessels & Jokonya, 2022). Ongori and Migiro (2010) stated that firms' digital transformation and ICT adoption contribute to good business strategies, creativity, and innovation, and enhance competitiveness, leading to a more competitive role and better profits in the globalized market, which helps SMEs.

2.4.2 Digital Technologies Reduce Costs

The point of innovations is to reduce transaction costs, and digital technologies such as blockchains and cryptocurrencies with smart contracts have the potential to do this significantly (Agmon, 2021). People can now conduct business and make financial transactions without using typical banking institutions and avoiding transactional bank fees or charges (Ather, Akhtar, Naqvi & Parwez, 2021). Hence, a digital workflow that does a similar job as an employee is faster and without human error, leading to lower operating costs (Abollado, Shehab & Bamforth, 2017). The deployment of digital technologies contributes to the servicification of the economy, a process in which goods are increasingly consumed as services by reduced transaction costs (Beaumier, Kalomeni, Campbell-Verduyn, Lenglet, Natile, Papin & Zhang, 2020; Zide & Jokonya, 2022). On this point, SMEs will succeed in the digitalized environment because it supports collecting information, cost reduction, and clientele expansion (Borges et al., 2009; Harrigan et al., 2011). Kandilov, Kandilov, Liu and Renkow (2017) stated that the reasons that drive SMEs' adoption of technology are mainly to reduce the costs of production and availability of labor, so that services are more efficient (Mellor, 2017; Jeffares, 2021). A substantial investment can be one of the most critical factors in business success in the long run. A lack of budget allocation hampers organizational decision-making and effective transformation programs. Businesses must have a long-term strategy and a solid capital plan (Grand View Research, 2022).

2.4.3 Digital technologies lead to Business Model innovation

The business model is becoming more widely recognized as a strategic asset for gaining a competitive edge and improving company performance. There is a well-established link between technology and the business model, and having more customers (Aloini, Latronico & Pellegrini, 2021; Dincă, Dima & Rozsa, 2019; Foss & Saebi, 2018; Davenport, 2013; Earl & Feeney, 2012). The quest for new strategies to create and capture value for business stakeholders and relationships in a specific geographic market is called business model innovation (BMI) (Aspara, Hietanen & Tikkanen, 2010). BMI refers to a company's latest operations system (Foss & Saebi, 2016; Garzella, Fiorentino, Caputo & Lardo, 2020), and innovative framework value development and value capture (Chesbrough, 2010), involving a single company and its partners and customers (Bouncken & Fredrich, 2016). Firms are being pushed toward new business models by digital technologies, making innovation more important (Garzella, Fiorentino, Caputo & Lardo, 2020; Kumar & Ayedee, 2021). Business model research has grown dramatically, with 7391 publications in the Scopus database from 1980 to 2015, and is rapidly increasing (Foss & Saebi, 2018). Digital technologies allow scientists to create knowledge that would otherwise be unachievable, and it may enable innovation management tactics (Lanzolla, Pesce & Tucci, 2021).

Digital technologies such as the Internet of Things (IoT), allow for remote monitoring and management of vehicles, machines, and process performance, facilitating service business models (Haaker, Nguyen-Thanh & Nguyen, 2021). Furthermore, digital technologies can improve companies' objectives by streamlining and integrating all business processes

(Fjeldstad & Snow, 2018). Academics and practitioners have addressed the relationship between digital technology and innovation, and they indicated that technology drives this (McAfee & Brynjolfsson, 2008). Digital disruption has accelerated across industries over the past decade, and digital technologies are driving companies to create new business models (Fjeldstad & Snow, 2018; Garzella, Fiorentino, Caputo & Lardo, 2020).

2.4.4 Digital technologies Support Decision-Making Processes

Digital technologies are used by businesses to respond to the ever-changing marketplace environment, which is very competitive. The decision support system (DSS) is a computerized system that assists with decisions, judgements, and actions in a variety of industries, professions and vocations, helping to increase revenues, reduce costs and save time (Zong, Yuan, Montenegro-Marin & Kadry, 2021; Alrawadieh, Alrawadieh & Cetin, 2021). Digital technology can transform the way judges work and provide for quite diverse types of justice such as videoconferencing, including internet-based group video conferences and email, which can supplement, support, and replace many face-to-face in-court procedures (Sourdin, 2018). Here, artificial intelligence is already helping to simplify administrative decision-making, e.g., the Mexican "Expertius" system, for example, is currently counselling judges and clerks on "whether the plaintiff is or is not entitled to granting him/her a pension" (Sourdin, 2018).

2.4.5 Digital technologies are Reducing Risk-Mitigating

Companies can minimize risks by reducing the likelihood of flow interruptions in the supply chain, mitigating operational risks that depend on operating costs (Garzella, Fiorentino, Caputo & Lardo, 2020). Big data analytics can enhance supply chain risk management and disaster resilience (Ivanov, Dolgui & Sokolov, 2019). Digital technologies enable firms to generate a measurable return on investment resulting from improved working conditions and culture, growth capture, and risk mitigation (Simmonds & Bhattacherjee, 2015). Lee, Phaal and Lee (2013) noted that mobility is crucial for most companies' business innovation agendas today. Digital technology assists SMEs' owners/managers discover, measure, and control various facets of their businesses, allowing for improved risk management using a digital system, and organizations' reputational, legal, and organizational risks and what to do about them become more apparent (Ortizde-Mandojana & Bansal, 2015).

Since the risks are calculated and shown in the integrated management framework, digitization is aided by the rising use of smartphones, mobile devices, and related applications. Organizations may use digital transformation to overcome risks and deal with disruptions, including market/industry fluctuations, corporate restructuring, and geopolitical climate, resulting in unexpected outcomes (Grand View Research, 2022). Furthermore, big data may help with risk assessment, decision-making support in real-time, reducing human errors, forecasting dangers, and increasing safety/security while lowering costs (Alawad & Kaewunruen, 2021). Since the outbreak of COVID-19, novel digital explanations such as consumer apps, intelligent CCTV, and big data for safety and health services may help social distancing and control stations, crowds, and train occupancy (Alawad & Kaewunruen, 2021).

2.4.6 Digital technologies Improve International Marketing

The digital technologies for international business have emphasized multinational firms' issues, notably managing interactions with a global platform and ecosystem partners. For example, consumer-facing and industry-facing platforms that use digital technologies like mobile computing, AI, Big Data Analytics, Internet of Things, and blockchain to create and deliver value to global customers have become essential vehicles for businesses, especially those in the manufacturing sector (Nambisan & Luo, 2021). Digital technologies' role as a complementary or even substitutional means of accessing international markets has been emphasized in research (Olejnik & Swoboda, 2012; Sinkovics & Sinkovics, 2013). A crucial factor in the digital transformation of business is the emergence of new local-global links of enterprises with other firms or customers (Galloway, Sanders & Deakins, 2011). Scalability refers to a company's ability to internationalize its business model by offering an additional platform for business partnerships or marketing and sales and growing awareness of global markets and potential competitors (Bianchi & Mathews, 2016). The benefits of digital technology can be even more significant for SMEs, as they can helo to mitigate internationalization pressures linked to having to compete with corporations and not having the same levels of financial and human capital (Tarutė & Gatautis, 2014).

2.4.7 Digital technologies Contribute to Flexibility

The notions of flexibility and dynamic assembly system design are at the heart of Industry 4.0 technology, and digital technologies improve demand capacity flexibility and responsiveness (Ivanov, Dolgui & Sokolov, 2019). Agostini and Nosella (2020) indicated that the Advanced

Manufacturing Technologies (AMTs) contribute to flexibility, shorter production cycles, and quicker responses to evolving market demands, better control, and precision of production processes (Caputo, Marzi & Pellegrini, 2016). Furthermore, digital technology is a crucial determinant for boosting production flexibility (Cugno, Castagnoli & Büchi, 2021). Firms in a range of industries can now operate as platforms. In uncertain and changing economic conditions, digital platforms are adaptive because they are flexible (Kiesling, 2021). Because of intelligent mobile technology, employees can use information and services offered by organizations without being confined to a single location (Alawadhi, Aldama-Nalda, Chourabi, Gil-Garcia, Leung, Mellouli & Walker, 2012). Abollado, Shehab and Bamforth (2017) write that streamlined handling of a workflow management system provides a good insight into all business processes and superior control, scalability and increased flexibility.

2.4.8 Digital technologies Improve Productivity and Growth

Digital technologies boost company productivity and contribute to the progress of enterprises, regions, and nations (Norris, 2020; Popović-Pantić, Semenčenko & Vasilić, 2020). Construction firms see new digitization trends as opportunities to increase their performance and productivity (Bosch-Sijtsema, Claeson-Jonsson, Johansson & Roupe, 2021). Martinez (2019) asserted that these technologies improve productivity and create new options to deliver better products to consumersm, while disregarding the digital transition will cause businesses to vanish (Seyitoğlu & Ivanov, 2020; Kumar & Ayedee, 2021). It must be note that the simple adoption of 'basic' digital technology may not be enough to produce marked productivity gains. Nonetheless SMEs that can combine these technologies with strategic marketing, operations, supply chain, or human resource management systems may realize significant improvements (Colombo, Croce & Grilli, 2013). Caballero-Morales (2021) recently wrote that digital technologies such as communication platforms (WhatsApp, ZOOM, Skype) are the most important facilitators for creating innovative products and maintaining their networks.

2.4.9 Digital Technologies are Developing Entrepreneurship

New forms of innovation, business models, new products, and the transformation of old businesses into new ones are leading to greater entrepreneurship (Reuschke, Mason & Syrett, 2021). Digital technologies greatly determine how new company initiatives are conceived and developed. The digital technology paradigm is making possible cooperation and collective intelligence between people who want to build an enterprise or long-lasting venture (Elia, Margherita & Passiante, 2020). The social boundaries of entrepreneurial activities are also altering because of digital transformations (Nambisan, 2016). Recent literature reviews show that digital technologies are a form of multifaceted form of entrepreneurship involving computer-related processes, education, and business strategies (Eller, Alford, Kallmünzer & Peters, 2020). Most digital entrepreneurial businesses have an international, and if not global, market reach due to the reach of digital technology (Kelestyn & Henfridsson, 2014). Examples include Airbnb and Uber, founded on digital platforms by entrepreneurs who saw new opportunities afforded by the new technology (Gabrielsson, Fraccastoro, Ojala & Rollins, 2021). Entrepreneurs and innovators embrace digital technologies to build new types of activities that go beyond conventional business boundaries to include networks, ecosystems, and societies, accelerating the evolution of new projects (Chandra & Leenders, 2012; Huang-Saad, Fay & Sheridan, 2017; Eller, Alford, Kallmünzer & Peters, 2020).

2.4.10 Digital Technologies are Building Virtual Models

Digital technologies make it possible to evaluate the functionality and performance of core and component products and processes through virtual models, and they can show future or actual physical industrial products from micro- to large-scale contexts (Yu, Han, Yang, Wang & Feng, 2021). These virtual digital forms make it possible to examine product or factory performance in various scenarios and less time is required for the production processes in highly competitive industries (Fatorachian & Kazemi, 2021). Furthermore, through real-time monitoring of operational conditions for essential resources, emphasizing efficient downtimes, and conveying them to operators via user-friendly devices, digital technologies reduce errors (Cugno, Castagnoli & Büchi, 2021). This type of monitoring enables quick action and the return of peak operating conditions (Georgakopoulos, Jayaraman, Fazia, Villari & Ranjan, 2016).

2.5 Digital Technologies Adoption Process

The digitalization process is a path consisting of initiatives carried out to implement modern technology (Martinez, 2019). Pumplun, Fecho, Wahl-Islam and Buxmann (2021) postulated that the adoption of innovations technology is divided into two stages: (1) initial readiness for technology; and (2) subsequent implementation within the organization. Both processes are critical to the success of technology within a company, and they should be treated as interdependent (Tornatzky & Klein, 1982). Dressler and Paunovic (2021) identified the paths to the digital transformation of businesses, and there are numerous and practical tools available to navigate these dynamic change capabilities. For example, there is the ability to sense digitally (filtering and evaluating digital opportunities), digital capturing capabilities (prototyping and defining the value proposition of a business model (BM)), and digital transformation capabilities (governing and aligning assets following innovation ecosystem). Organizational implementation is the process through which a company adopts a new idea to gain competitive advantages such as higher productivity, bigger profits, strategic dominance, efficiency, and effectiveness (Talukder, 2014).

Martinez (2019) stated that the textile industry in which many SMEs operate, provides examples of technology application. He claims that textiles firms in China are introducing more Enterprise Resource Planning (ERP) systems compared to India. Nevertheless, businesses in India incorporate more Customer Relationship Management (CRM) techniques than their counterparts in China. In this scenario, cultural variations in the digitalization paths between the two countries determine diversity of products being sold. The research does not provide a strategy to implement or a learning experience that encourages other businesses' digital transformation. In an organization, information technology expertise, skills and operations will only exist if that enterprise prepares a platform that will work well for all personnel, administrators of hardware, software, and human resources, etc. (Popović-Pantić, Semenčenko & Vasilić, 2020).

The adoption process is a series of steps that a potential adopter must complete before accepting an innovation (Talukder, 2014). Mazzarol (2015) pointed that literature focused on business organization mainly aims to examine the digital transformation process by analyzing the implementation, distribution, and deployment of digital technologies using three steps firstly; conducting marketing and promotional activities (e-marketing); secondly, conducting transactions such as business to business and business to consumer (e-commerce); and thirdly, enhancing manufacturing processes, customer correlation process and inside management processes (e-business). Using sociological theory, Rogers proposed that each potential adopter's assessment of these characteristics is crucial to the acceptance decision. Rogers (2003) defines adoption as the decision to utilize innovation fully as the best course of action. This study will focus on the idea that an organization's embrace of digital technology may have been taken in the last two steps of Rogers' innovation adoption model. However, confirmation will be determined by how SMEs integrate innovation in their daily routines and relevant activities. The projected benefits may not be realized if SMEs' owners and managers are not interested in this possibility. As a result, it is critical to consider what motivates business owners and managers to embrace and maintain innovative practices.

2.6 Digital technologies in Jordan

Jordan sees digital transformation as a foundation for the country's economy. The country's Ministry of Digital Economy and Entrepreneurship (MODEE) is responsible for the digital economy and entrepreneurship, building on the country's achievements in the ICTs industry. MODEE will work on in collaboration with other government agencies, such as digital infrastructure, digital leadership, digital platforms, digital skills, and digital financial services (MODEE, 2021). In Jordan, digital transformation necessitates a common ground based on enabling information and communication technology (Lukonga & Joshi, 2020). The most critical problems that affect IT project efficiency in Jordan are poor preparation, a lack of goals and objectives, and changing project objectives throughout project execution (Alkhlaifat, Abdullah & Al-Khamaiseh, 2021).

Subsequently, the digital transformation vision (REACH 2025) is critical for Jordan's future economy, enabling individuals, industries, and businesses to adopt digital solutions and establish a solid foundation. Jordan's government unveiled the REACH 2025 Vision in 2016, and it has taken several significant steps to transition industries, businesses, and individuals to becoming virtually digital by 2025 (Adaileh & Alshawawreh, 2021). Jordan is gradually shifting away from perceiving ICTs as a separate industry, and now digitizing the whole economy while focusing on specific markets and global value chains (Adaileh & Alshawawreh, 2021). However, Awajan, Arafat, Al-Shalabi, Awajan and El-Omari (2013) reported that despite the rapid growth in the world's use of ICTs, e-business activities in Jordan and most developing countries are still limited and only slowly evolving. They said Jordan was placed 51st in the world according to the micro-index ranking in e-Commerce, and Jordan is placed 4th in the Middle East region, scored at 4.42 of 10 after Israel, the United Arab Emirates and Turkey.

Turan, Uğur and Palvia (2020) reported that networks and communications, business intelligence and analytics, business process management systems, collaborative and workflow software, and extensive data systems are the top five critical organizational IT problems in Jordan, and no company and especially SMEs can afford to disregard these technologies. Brits and Cabolis (2019) stated that according to the 2019 world digital competitiveness ranking, Jordan was in 63rd place for IT integration, 59th for e-government, 30th for public-private partnerships rank, 19th for cybersecurity, 46th for software piracy, 42nd for communications technologies, 30th for mobile broadband subscribers, 25th for wireless broadband, 48th for Internet bandwidth speed, and 62nd for high-tech exports. According to Adaileh and Alshawawreh (2021), revenue growth across the digital economy sectors will climb by 25-30% by the year 2025 in Jordan.

A significant force behind change and innovation in our society and economies is the digital transition, which has been further pushed by COVID-19. Jordan and other Middle Eastern economies have prioritized advancing the digital transformation agenda in recent years. Additional investments in the digital sector could boost growth along with the necessary organizational reforms. Compared to a global average of 4.5% to 15.5%, the Arab region's digital economy today contributes only about 4% of GDP (OECD, 2022). Costly ICT and a lack of supporting infrastructure. In the Arab world, Jordan has the highest fixed broadband bundle, mobile voice, and mobile data costs and taxes. This has resulted in poor service, which has slowed the development of digital payments and mobile e-commerce (OECD, 2022). Additionally, there is a need for significant investments in IT infrastructure, including those for cloud services, fibre optics, IoT, extending 4G, and launching 5G, among other things. Although Jordan's legislative framework for ICT regulations is relatively sound, it is difficult to put rules and regulations into practice and understand them correctly (OECD, 2022). They are frequently open to the interpretation of officials, which has harmed the predictability of the current business climate. The ICT industry plays a bigger role in Jordan's economic growth. Its contribution is about 4% of the GDP, it has between 600 and 900 businesses, most of which are micro, small, or medium-sized enterprises, and is one of the fastest-growing sectors in Jordan (MODEE, 2021). Jordan also has one of the highest regional Internet penetration rates and more than any other sector of the economy, the ICT and IT-enabled services sectors collectively have the most significant rate of employment for women, which is 33% (OECD, 2022).

The wave of liberalization reforms in 1999 allowed Jordan's ICT sector to increase and attract many investments from the private sector. Today, with one of the most significant concentrations of IT firms in the Arab world, Jordan is a regional hub for ICT investments in MENA (Privacy Shield Framework, 2022). Jordan is desirable for investors serving local and regional ICT markets due to political stability, advantageous geographic location, abundant university graduates, and a comparably mature ICT sector. Global ICT powerhouses, including Cisco, Expedia, HP, Microsoft, and Oracle, are among them (OECD, 2022). The imbalance between the demand and supply of ICT skills in Jordan is one of the main obstacles for investors. Only about 7.5% of the 8000 annual graduates with an ICT specialization work in their field, for example. This could be caused by several things, such as the academic community's poor comprehension of market demands and graduates' lack of English language skills necessary for ICT jobs (OECD, 2022). Furthermore, a lack of soft skills, an obsolete university curriculum, a lack of knowledge of current global technological trends, little to no practical hands-on experience, and brain drain to neighbouring nations are further contributing causes to the skills gap. Updating curricula is challenging because of governmental regulations, compliance requirements, and accreditation procedures (World Bank, 2019). To overcome the skills gap, high unemployment, and brain drain, upskilling and reskilling local people, engineers, recent graduates, and women could be helpful. as part of the World Bank's Youth, Technology, and Jobs project from 2020-2025 (OECD, 2022).

2.7 Small and Medium-Sized Enterprises (SMEs)

SMEs are driving the growth of the global economy (Chege & Wang, 2020). SMEs are essential for developing and emerging economies, and this sector is at the centre of government policies in developed and developing nations, and even inspiring research (Otman, 2021). In the late 1940s, the definition of small and medium-sized enterprises (SMEs) was guided by issues such as economic circumstances, bank credits, new tax terms, etc. (Chung & Au, 2021). Definitions of SMEs have been created reflecting a country's economic, cultural, and social assumptions and traditions, and are often based on size or turnover (Katua, 2014). SMEs have been pillars for skills development, poverty reduction, economic progress, people's empowerment, and employment (Chege & Wang, 2020). Studies have established certain criteria for SMEs based on the number of people working in them, total assets, sales turnover, and in 2011 the World Bank report estimated there were at minimum 400 million SMEs throughout the world (Otman, 2021). However, it is challenging to define SMEs since there is no fixed definition (Kumar & Ayedee, 2021). Zulu-Chisanga, Chabala and Mandawa-Bray (2020) postulated that 99% of businesses in developing countries are SMEs. SMEs account for 60% of industrialized countries' economies, while they account for 99% of businesses in developing countries (Muriithi, 2017). Rao, Kumar, Chavan and Lim (2021) stated that SMEs account for 60-70% of employment and 55% of GDP and 90% of global GDP, highlighting the significance of SMEs as drivers of economic growth now and in the future. Furthermore, the World Bank predicts that 600 million people will enter the global labor force over the next 15 years, primarily in Asia and Africa (Otman, 2021). Mashal (2018) explained that due to their capacity to increase productivity and their complex ties with many productive sectors in society, SMEs can help overcome economic and social problems. They assist in reducing unemployment, growing productivity, and generating income in Arab countries in the Middle East and North Africa (Alkhodary, 2021; Mashal, 2018; Chege & Wang, 2020; Muriithi, 2017). The most significant barriers SMEs face are access to loans, management skills, very high tax rates, great use of energy, unfair competition, and political factors (Otman, 2021).

2.8 Small and Medium-Sized Enterprises (SMEs) in Jordan

Jordan is situated in southwest Asia, and it covers 92,300 km^2 of territory with ten million people (Nations Encyclopedia, 2021). Officially known as the Hashemite Kingdom of Jordan, it is located on the Jordan River's East Bank, hence its name. Jordan is a semi-arid country and geographically positioned at the intersection of Asia, Africa, and Europe. Amman is Jordan's most populous city and the country's economic, political, and cultural centre. In developing countries, most people depend heavily on SMEs for their jobs and income. For these reasons, economic decision-makers in both developed and developing countries, including Jordan, deem SMEs to have a central role in the economy and enhancing investment, social growth and cohesion (Saymeh & Sabha, 2014; Mashal, 2018; Zulu-Chisanga, Chabala & Mandawa-Bray, 2020). Moh'd AL-Tamimi and Jaradat (2019) indicated that SMEs in Jordan make up 98% of all firms, so they are hugely important to economic growth. Mkhaiber and Werner (2021) asserted that one of the primary impediments to Jordanian SMEs' development is a lack of access to finance or loans. Betz and Frewer (2016) wrote that Jordan is an upper-middle-income economy with a GDP per capita of US$5,600 in 2015.

In recent years, the Syrian and Iraqi conflicts have greatly threatened the economy, disrupting trade routes, reducing tourism, investment, and imposing additional refugee assistance costs. A few years ago the *Jordan Times* newspaper (2019) stated that SMEs are working rigorously to modernize their technology and boost their competitiveness in the face of ever-growing competition. The OECD (2019) reported that SMEs in Jordan were defined as enterprises that employed up to 250 persons as stated by the Jordanian Ministry of Industry (Mashal, 2018). This is in line with global practice elsewhere in the world, especially in the European Union and in many OECD member and partner countries. Jordan's SMEs play a key in economic growth and their numbers and employees are summarized below in Table 2.

Table 2: Classification of Jordanian SMEs

Category	**Capital Investment (JD)**	**Number of employees**
Micro	Less than 30,000	1 – 4
Small	30,000-300,000	5 – 19
Medium	300,000-3,000,000	20 – 99

Resource: Mashal, 2018.

Mashal (2018) wrote that Jordanian SMEs are struggling and have been for nearly twenty years, due to their limited ability to access capital. This claim is backed up by other research (Saymeh & Sabha, 2014). According to OECD (2019) SMEs can become critical drivers of Jordan's development. Jordanian SMEs' productivity and performance are limited and weak. For instance, over 54% of those working in SMEs with less than four employees in the service sector are unpaid (e.g., family members), compared to only 8% in companies with 5 to 10 employees and 0.23% in companies with 20 or more personnel (Betz & Frewer, 2016). Nevertheless, SMEs in Jordan contribute 40% to the GDP and account for 45% of total exports. The matrices indicate the expected outcomes for each action and operation, the responsible parties, the start date and end date, resources needed, and leading performance indicators (OECD, 2019). According to Jordan Enterprise Development Corporation JEDCO (2020), to drive its economy, Jordan relies almost entirely on small and medium-sized enterprises and roughly 98% of all companies are listed as SMEs, of which two-thirds have less than 19 workers. It is important to note that SMEs overcome multiple these obstacles which vary depending on the nature of the business. New business owners suffer from insufficient financing/loans, weak products, ineffective marketing and the lack of sufficient incentives compared to international corporations.

The OECD (2019, p. 78) implemented the project "SME Policy Effectiveness in Jordan" which was sponsored by it and the Jordan Enterprise Development Corporation (JEDC) from 2016-19. This project helped to enhance SME and Entrepreneurship Policymaking by improving institutional alignment and dialogue, advocating better tracking and evaluation of policies and services, and finding ways to improve business policy and statistics on entrepreneurship. The key outcomes of the project were three User Guides. User Guide 1: Improving SME policy coordination and public-private dialogue offers SME policy coordination guidelines and orchestrating efforts among the many actors who help SMEs. User Guide 2: Successful SME and Entrepreneurship Policy and Policy Tracking and Assessment the services guide determining the effects of SMEs' assistance. User Guide 3: SME statistics and entrepreneurship metrics provide valuable guidance for strengthening SME policymaking evidence. These three user guides draw on international experience and practice to provide Jordan with areas where action is needed. They may be of interest to other countries seeking to improve the efficiency of their SME policymaking processes, supported by the MENA transformation fund, and the Secretariat jointly implemented the project for foreign affairs, the Centre for Entrepreneurship, SMEs, Regions and Cities, and the Statistics Department in Jordan and the OECD Data Directorate. The government of Jordan wants to expand SMEs but there is no coherent strategy, or a mechanism for designing and tracking how progress will be made (Al-Tamimi & Jaradat, 2019; Moh'd Al-Tamimi & Jaradat, 2019). Nevertheless, Jordan has made good progress in some areas while decreasing its fiscal deficit. As well the government in Jordan is focusing on its Economic Growth Plan 2018-2022, which aims at enhancing the business environment (Al-Naimi, 2021).

2.9 Digital technologies and Small and Medium-Sized Enterprises

The rising amount of academic research covering digital technology focuses predominantly on large businesses (Eller, Alford, Kallmünzer & Peters, 2020). Digital technologies have significantly changed the business and marketing environments. Whether this presents a prospect or a challenge for SMEs depends on how these organizations consider it strategically (Quintona, Canhotoa, Molinillob, Perac and Tribikram Budhathokid, 2018). Most SMEs adopt a short-term strategy compared to larger firms (Moeuf, Pellerin, Lamouri, Tamayo & Barbaray, 2018). SMEs are projected to use technology-based innovation to improve their productivity and efficiency because of increased mobile phone and internet usage throughout the world (Trinugroho, Pamungkas, Wiwoho, Damayanti & Pramono, 2021). According to OECD (2017), digital technology's acceptance remains exceptionally low among SMEs, even for technologies like cloud computing. To express organizational changes made possible by digital technologies, academics and industry employ the term "digital transformation" (Burki, 2018). Gupta, Seetharaman and Maddulety (2020) note an increase from 50% to 90% in technology adopters. Joensuu-Salo Sorama, Viljamaa and Varamäki (2018) asserted that in practically any new venture or SMEs, digital technology could expand, strengthen, and enrich boundary-spanning interactions, and the implications of digitalization on the internationalization SMEs are profound. As it is becoming increasingly important for SMEs to look beyond their national markets for growth, the global economy's growing digitalization provides them with sufficient internationalization opportunities (Joensuu-Salo, Sorama, Viljamaa & Varamäki, 2018).

Westerlund (2020) shows that internationally focused online SMEs differ from domestically oriented ones in terms of a higher level of: (1) usage of information systems, (2) magnitude of value networks, (3) focus on critical internal services, and (4) addressing cybersecurity issues. Online SMEs can function globally and build a range of skills in terms of alliances, customer relationships and management of business processes, as well as good investment in ICT tools and cyber resilience. Thus, companies from all industry sectors are researching new ways of using digital resources and technologies. Several traditional industries are now engaging in modern digital technologies such as data analysis, digital communication, connected objects, intelligent devices (Pagani & Pardo, 2017). Gamache, Abdulnour and Baril (2019) stated that the HUB Institute created a blueprint to help organizations conduct digital transformation, taking the form of a business strategy. Six key dimensions must be discussed, these being leadership, community and organization, technology management, data management, evaluation framework (decision-making) and customer experience (Gamache, Abdulnour & Baril, 2019).

The literature on digital technology with an emphasis on SMEs is still in its nascent stage. Icks, Schröder,Brink, Dienes and Schneck (2017) identified four explanations for understanding why digital transformation is slow in SMEs, and these are based on a handful of studies looking at the effect of digitalization on SMEs. Firstly, small businesses with a particular emphasis are industries less vulnerable to the need for rapid digitalization. Secondly, to truly appreciate digital transformation implications, small businesses frequently lack capital and managerial vision. Thirdly, in contrast to larger organizations, SMEs typically take an incremental approach to digitalization. Last, digitalization investments within this type of company heavily rely on financial performance and what to do with limited resources (Gruber, 2019). Von Leipzig et al. (2017) demonstrate a lack of digitalization-related technologies and expertise a poorly organized plan, may also be a lost opportunity, which is not helped by financial obstacles. As Goerzig, Luckert, Aichele and Bauernhansl (2018) stated, the human side must always be considered and digitalization in SMEs depends on employees driving this. To stay competitive or even find new markets, SMEs need to be prepared to adapt to their new technology (Safar, Sopko, Bednar & Poklemba, 2018; Goerzig, Luckert, Aichele and Bauernhansl (2018). It has been assumed that the agility and versatility in strategy can be accomplished by using advanced technology.

The Internet now offers SMEs access to various technologies and applications through cloud services, including big data analytics, helping businesses solve problems at a much lower cost than ever (OECD, 2017). It is crucial to encourage SMEs employ digital technologies because they can help overcome some of the traditional barriers, including the often-high cost of these investments, and allowing them to switch more quickly from one technology to another. The introduction of such emerging innovations can also be fostered by pro-competitive commodity sector regulations and job security legislation that is not excessively restrictive to help smaller firms compete with larger, existing incumbents, policies that promote workers' mobility, training and skills growth, which are essential (OECD, 2017, p. 9). SMEs need guidance in their digitalization strategies to keep pace with changes in technology, and they can take place by prioritizing what needs to be done (Dethine, Enjolras & Monticolo, 2020). Caballero-Morales (2021) demonstrate that digital resources such as the Internet and communication platforms (WhatsApp, Zoom, Skype) will help SMEs maintain their networks and create innovative products or goods and services, ultimately assisting them in surviving during and after COVID-19. SMEs have limited technological and financial resources, but government assistance and policies will likely be more effective in convincing them to accept new digital technologies (Park & Kim, 2021; see Bai, Quayson, & Sarkis, 2021). While digital technologies are one of the keys to business continuity, SMEs in developing countries do not appreciate the benefits of ICT due to the lack of knowledge and limitations that follow its investments (Abeh, Talib & Amoako, 2021). In the next section, we will describe the concept of digitalization and how it shapes the performance of SMEs.

2.10 Digital Technologies impact SMEs' Performance

Digital technologies profoundly affect economies and communities and change how we work, connect, participate, and enjoy ourselves in social activities. In several different fields of life, they also drive creativity. Many studies have noted the importance of technology adoption and capabilities for SMEs (Zhou, Gao & Chimhowu, 2019; Hansen & Bøgh, 2020; Räisänen & Tuovinen, 2020; Trinugroho, Law, Lee, Wiwoho and Sergi, 2021; Kumar & Ayedee, 2021). In Australia, the United States and the United Kingdom, studies found that companies and associated service operations are substantially more efficient than those not using ICT (Ibidunni et al., 2018). Ramsden (2010) suggested that the difficulties and variables affecting the performance of SMEs vary from country to country as follows: 1) government regulations (how simple the procedures are to set up and close an enterprise and acquire the requisite licences and permits for functioning); 2). innovation and preparation (the opportunity to build ideas and skills for entrepreneurs and workers; 3) corruption; 4) financial support (how to get access to credit, loans, etc.).

Kohli (2017) points to previous research indicating that market orientation's impact on business performance is positive in contexts characterized by varying levels of market volatility, competitive intensity, and technical turbulence. Ismail, Omar, Soehod, Senin and Akhtar (2013) describe the obstacles to SMEs' growth and understand what factors hinder their survival; the authors concluded that labor skills, government policies, strategy and competition are the external environmental factors that are critical here. Other determinants are likely to mediate digital technology's impact on SMEs' performance, since digital transformation involves investing in technologies and incorporating them into the procedures, and then seeing what they do for product or process innovations, new marketing strategies, and changes in routines/procedures both within the company and between companies (Lu & Xu, 2018; Kumar & Ayedee, 2021).

The world of the workplace is also changed by these digital technologies, producing entirely new forms of digital or virtual labor, both paid and unpaid (Valenduc & Vendramin 2017). Jepsen and Drahokoupil (2017) remark that digital technologies are changing the job market, skill requirements, how work is structured, incomes and the tax base. A study by Autio and Thomas (2016) suggested that digital technologies boost these interactions' capacity to co-create value by improving business (through easier accessibility and efficiency), extending and enriching them (through greater data intensity) (beyond the core exchange of goods and services). Joensuu-Salo, Sorama, Viljamaa and Varamäki (2018) explained that some businesses have digitalized their production processes or developed new revenue models according to the arising opportunities (see Kohli, 2017).

The benefits of digitalization for SMEs have been clearly stated by the OECD (2017) in terms of better access to knowledge and talent, expanded consumer access, more access to finance, better collaboration and communication, greater access to technology and applications, broader product development and reduction of red tape. According to Verhoef, Broekhuizen, Bhattacharya, Dong, Fabian and Haenlein (2021), consumer expectations and habits have been fundamentally altered due to digital transformation and business model innovation, exerting tremendous pressure on established businesses and disrupting multiple sectors. They argue that digital transformation changes organizational structures and has implications for performance measurements. IT expertise an workers' ability to use ICT will help build new values and outlooks so managerial skills in information technology are strongly emphasized (Rockart, Earl & Ross, 1996).

Numerous studies assert that there is a positive relationship between market orientation and organizational performance in SMEs (Cano, Carrillat & Jaramillo, 2004). ICTs have not led to higher unemployment over time as was once feared, but instead to consolidation and reallocation of tasks (Brynjolfsson & Hitt, 2000). What will result is better efficiency, which eventually translates into cheaper new goods and services, higher demand for them, more jobs, thus reversing the initial loss of employment (OECD, 2017). Yet, empirical studies have reported mixed outcomes for the impact of digital technologies on various performance indicators, with several businesses continuing to fall into what has been called the efficiency paradox of information technology (Biagi, 2013). The degree to which digital transformation investment translates into improved economic performance remains difficult to make definite conclusions about (Calvino & Virgillito, 2018).

Moreover, Khayer, Talukder, Bao, and Hossain, 2020) asserted that the likelihood of large firms having more financial and labor resources could lead to discrepancies in company performance. Bouwman, Nikou and de Reuver (2019) argued that the outcomes of two methodological methods showed that SMEs could take numerous routes to improve their performance when their business model evolves through digital transformation. Bai, Quayson and Sarkis (2021) asserted that managers in SMEs and other stakeholders rethink their business strategies, incorporating crisis scenarios and continuity plans to retain customers so that digital development is viable, and they propose additional research areas in this area given the great changes caused by COVID-19. Gamache, Abdulnour and Baril (2019) asserted that management commitment improves digital output and facilitates a digital transition in SMEs (Masood & Sonntag, 2020; Kumar, Singh & Dwivedi, 2020; Kumar & Ayedee, 2021).

2.11 Conclusion

This chapter has examined the relevant literature on the adoption of digital technology in Jordanian small and medium-sized enterprises and its effect on how well their function. The literature review shows that digital technology refers to systems or tools new to SMEs so that they have the means to produce added value or enhance their business activities. The chapter discussed definitions of digital technologies and related typologies, the benefits of adopting digital technologies in SMEs from several aspects and highlighting the state of digital technology usage in Jordan. The review also looked at various aspects of the digital technology adoption process, which states that every process passes through key stages before acceptance becomes generally widespread. Finally, the measures that the company carries out to incorporate digital technologies were explained. The latest literature offers potential sources for exploring similar ideas or methods taken by organizations to incorporate the latest digital technologies. The following chapter explains the theoretical framework and methods for analysing digital technology adoption.

CHAPTER THREE: THEORETICAL FRAMEWORK

3.1 Introduction

This chapter discusses the theoretical framework devised for the thesis. The chapter provides a detailed overview of significant theories and models regarding the adoption of digital technologies and innovation. Theories and models will be discussed in the following sections include the following: theory of reasoned action (TRA), theory of planned behavior (TPB), the technology acceptance model and its extensions (TAM), technology acceptance model 2 (TAM2), diffusion of innovations (DOI) theory, unified theory of acceptance and use of technology (UTAUT), technology organization environment (TOE) framework, electronic data interchange (EDI), DeLone and McLean information systems (IS), combined (TAM) and (TPB), motivation theory, model of PC Utilization, social cognitive theory (SCT), technology readiness index (TRI), resource-based view (RBV), knowledge-based view (KBV) and institutional theory. Furthermore, this chapter will briefly discuss the limitations, suitability, justifications, and adoption of theories and models. The aim here is to establish a model of adopting digital technologies that incorporates certain variables devised in previous models, one that can explain the implementation of digital technologies by SMEs.

3. 2 Theory of reasoned action (TRA)

Fishbein and Ajzen in 1975 proposed the TRA (theory of reasoned action) model (Sumiati, Widyastuti & Takidah, 2021; Kumar & Ayedee, 2021). TRA has been widely used in applied research settings covering a range of subject areas, and the theory of reasoned action has also stimulated analysis of different refinements and extensions (Bagozzi, 1981; Saltzer, 1981). TRA is a unique and suitable model that predicts and understands human behavior (Talukder, 2014). It is implied they are just as crucial as Ajzen and Fishbein (1980) argued that investigating the impacts of external variables can improve understanding a particular behavioral phenomenon. It became a widely researched psychology model dealing with the determinants of consciously planned behaviors and as the name implies, from the psychology perspective (Milly, Xun, Meena & Cobbinah, 2021; Kumar & Kalse, 2021).

TRA is the basis of all the models developed since then. It states that behavioral intention (BI) is a measurement of the strength of one's intention to conduct a particular behavior or action (Davis, Bagozzi & Warshaw, 1989; Kumar & Kalse, 2021). Moreover, understanding how people incorporate technology into their everyday lives (TRA) looks at attitudes, subjective norms, intentions and actions (Peslak, Ceccucci & Sendall, 2012; Sumiati, Widyastuti & Takidah, 2021). A distinction between values, perceptions, intentions, and behaviors is the basis of the TRA conceptual framework (Al-Gahtani & King, 1999). Kumar and Kalse (2021) asserted that attitude toward and subjective norms are components of behavioral intents. The theory is based on the premise that people are generally very logical and that they can make use of knowledge available to them routinely (Ajzen & Fishbein, 1980). The theory's ultimate objective is to predict and understand an individual's actions (Talukder, 2014). Li (2010) asserts that TRA is based on the premise that people are rational decision-makers who develop their attitudes guiding their behaviors, and continuously quantify and analyze the related behavioral beliefs. Figure 3.1 illustrates the TRA model.

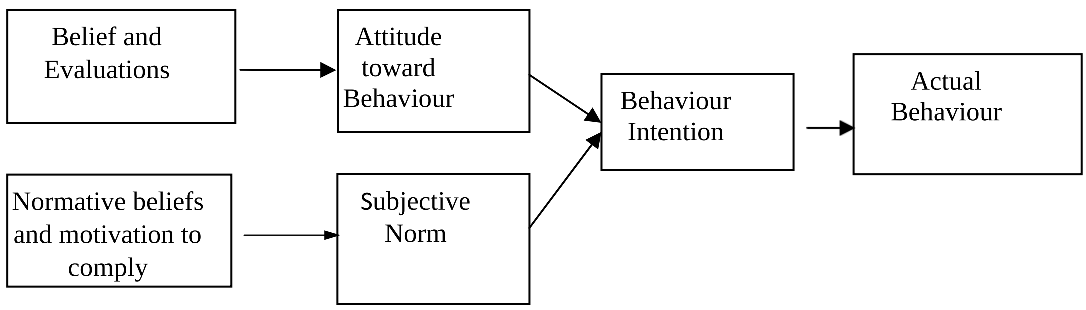


Figure 3.1 The Theory of Reasoned Action (Source: Fishbein and Ajzen, 1975).

Fishbein and Ajzen (1975) asserted that identifying attitude refers to the positive or negative feelings of an individual (evaluative effect) about enacting a behavior. Kamble, Gunasekaran and Arha (2019) proposed based on TRA that people are more likely to generate motivations if they have a positive attitude about an issue or subject, and their peers and significant persons anticipate them to undertake this behavior. TRA action was founded on integrating a variety of previous attitude-based theories such as learning theories, expectancy-value theories, consistency theories (Kamble, Gunasekaran & Arha, 2019). It is an exceptionally well-researched model that can predict and explain behavior across many contexts (Kukafka, Johnson, Linfante & Allegrante, 2003). In contrast, external and demographic influences are evidence that conduct is affected (Ajzen & Fishbein, 1980). TRA is a general model and as such, the operative beliefs for a particular behavior are not specified. Therefore, TRA researchers must first identify the essential ideas about the conduct under investigation (Davis, Bagozzi & Warshaw, 1989). Ajzen and Fishbein (1980) note that external variables can affect a person's beliefs compared to attitudinal and normative considerations. Their arguments show that external factors can affect behavior.

TRA has some limitations in describing all the mechanisms of actual innovation usage and the role of individual behavioral intention, as discussed in the related scientific literature (Rannenberg, Royer & Deuker, 2009). This theory has been used to study consumer behavior or other sorts of family planning behavior, and it is very reliable. It provides a view at the individual level but is not easy to apply at the organizational one (Kumar & Kalse, 2021). Ajzen and Fishbein (1980) noted that external variables could explain behavioral phenomena. Davis (1989) extended the TRA by offering two variables: perceived usefulness and ease of use to trace the effect on values, behaviors and intentions of external influences. Regarding the acceptance behavior concerning computers and related technologies, these variables were relevant. Ryan (2012) refined the theory to understand the processes that efficiently explain innovation and the effects of various approaches on behavioral intentions. This study acknowledges the work done by Ajzen and Fishbein (1980) on external variables' influence. It builds on their model using external variables whereby the TRA model does not include external determinants. This study expands the TRA model by including external variables and demographic determinants.

3. 3 Theory of Planned Behavior (TPB)

Theory of Planned Behavior (TPB) which was devised by Ajzen (1985) built on TRA theory for application to mandatory situations (Kamble, Gunasekaran & Arha, 2019). Basically, it functions as a theoretical framework to describe and predict human behavior in various decision-making processes (Taufique & Vaithianathan, 2018). TPB is a psychological theory that delves into the psychological underpinnings of human behavioral intention (Abbasi, Kumaravelu & Singh, 2021). The Theory of Planned Behavior (TPB) is similar to TRA in that TPB often claims that rational decision-makers are individuals (Li, 2010). The volitional and non-volitional control aspects are well thought-out explanations for a person's behavior, and according to this idea, individual or repeated intentions are the driving force behind human behavior (Abbasi, Kumaravelu, Goh, & Singh, 2021). For example, a person's preparedness or willingness to return to the same destination is defined as a revisit intention (Tosun, Dedeoglu & Fyall, 2015).

The TPB deals with situations in which people do not have complete control over their actions (Kamble, Gunasekaran & Arha, 2019). It is commonly used to simulate the adoption of a wide range of new information technology products, as well as to predict usage levels (Ma, Hipel, Hanson & Liu, 2018). TPB has been increasingly referred to in empirical studies to explain consumption and social psychology scenarios (Alam & Sayuti, 2011). It has also been used extensively to consider the individual's acceptance and usage of various technologies (Harrison, Mykytyn & Riemenschneider, 1997). The TPB model has been widely embraced in the literature to explain consumer behavior in various contexts, including the use of smartcards, artificial intelligence to make financial investments, self-service technologies (Belanche, Casaló & Flavián, 2019; Lien, Hsu, Shang & Wang, 2019), and mobile payment plans (Flavian, Guinaliu & Lu, 2020). TBP seeks to understand how external influences such as social norms and perceived control effects affect an individual adopter's internal decision-making process (Montes de Oca Munguia, Pannell & Llewellyn, 2021). Figure 3.2 illustrates the Theory of Planned Behavior (TPB) model.

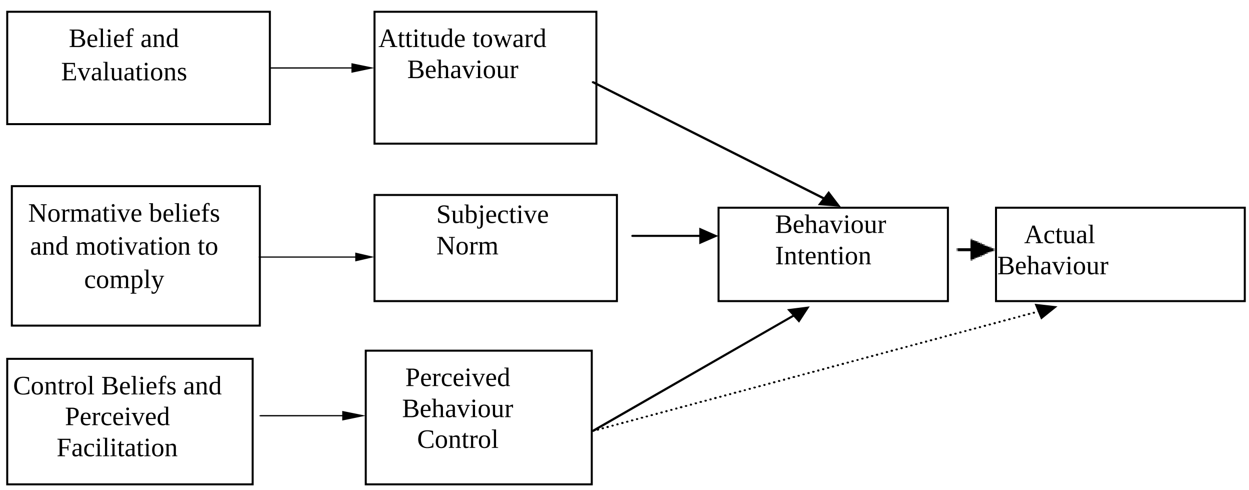


Figure 3.2 The Theory of Planned Behavior
(Source: Ajzen, 1991).

Yoo (2021) claims that intention is founded on three key antecedents: attitude, subjective norms, and perceived behavioral control in the TPB paradigm. The first indicator of intention is an attitude, which captures an individual's overall assessment of behavior performance. Subjective norms refer to the sway that influential persons have over decision-making. These factors influence whether a person will engage in each type of conduct. Perceived behavioral control, the third predictor of intention, suggests an individual's opinion of how easy or difficult it is to accomplish a specific action (Yoo, 2021). Internal control connected to self-efficacy (e.g., skills, capabilities, and willpower) and external control related to environment/controllability (e.g., time, opportunity, and reliance on others) are the two key dimensions of perceived behavioral control (Barua, 2013). The TPB model's most significant issue is not that enough variability in behavior is not clarified. The critical problem is that some of the theory's propositions are incorrect (Taylor, Bury, Campling, Carter, Garfied, Newbould & Rennie, 2006).

The TPB addresses cases where people do not have complete control over their behavior, subjective norms, desire to use and actual use, which are the different TPB frameworks (Kamble, Gunasekaran & Arha, 2019). Perceived behavioral control is characterized as "perceptions of internal and external constraints on behavior in the context of information system study" (Taylor & Todd, 1995). A perceived construct called perceived behavior regulation often requires more TPB. The observation's control factor is integrated into the model, making the TPB more effective in its implementation (Kamble, Gunasekaran & Arha, 2019). TPB is commonly used to model the reception of a range of new IT products and forecast levels of their acceptance (Issa & Hamm, 2017; Xie, Song, Peng & Shabbir, 2017; Ma, Hipel, Hanson, Cai & Liu, 2018). The mediation assumptions in the TPB conflict with the proof, beliefs are also found, for instance, to predict behavior above and beyond a person’s intentions (Araújo-Soares, Rodrigues, Presseau & Sniehotta, 2013; Conner, Gaston, Sheeran & Germain, 2013). TPB theory does not consider other factors influencing behavioral intention and motivation, such as anxiety, anger, mood, or previous experiences. The behavior is believed to be the outcome of a decision-making process that does not change over time (Edberg, 2013). TPB eliminates the factor of perceived risk from individuals' perceptions (Abbasi, Kumaravelu, & Singh, 2021).

However, the theory does not discuss the time between intent and behavior action. The TPB is more applicable to healthcare issues and values (Tucker & Grimley, 2011), but its capacity to account for environmental and economic factors is restricted. Abbasi, Kumaravelu and Singh (2021) stated that several researchers suggested that combined variables be added to TPB's framework original model to improve its predictive power with other behavioral theory components to create an integrated model (Meng & Cui, 2020; Meng & Choi, 2019; Soliman, 2019; Russell, Young, Unsworth & Robinson, 2017). TPB fails to document enough variance in intended behavior (Zailani, Iranmanesh, Masron & Chan, 2016). Yoo (2021) states that TPB does not entirely account for a significant amount of variation in intentions. According to Ajzen (2015) this difficulty might be solved by extending the TPB model to include extra factors in a specific context, which would increase the model's predictive power for people's intentions in that environment.

Subsequently, the model developed in this study tackles the components of normative beliefs and social norms involved in embracing technology. Subjective norms affect specific behavior from important persons - normative referents (Ajzen, 1991). For example, the variable concerning peers' influence was adopted by Taylor and Todd (1995) in their combined TAM and TPB model. In the proposed model the variable peer support in a socio-cultural context is motivated by an individual adopting a technology, which changes their perception of it. This study adopted Yoo's (2021) recommendation that researchers extend the TPB model by including more predictor variables (e.g., personal characteristics, gender) to develop a more holistic perspective.

3.4 Technology Acceptance Model (TAM) and Its Extensions

The technology acceptance model (TAM) was posited by Davis in 1989 (Chatterjee, Chaudhuri, Vrontis & Basile, 2021; Al-Gahtani & King, 1999) but in fact derived from reasoned action theory (TRA) (Yoo, 2021; Kumar & Ayedee, 2021). It suggests that two significant variables decide the use of an information system: perceived usefulness and perceived ease of use are relevant for computer acceptance behaviors (Davis, 1989; Yoo, 2021; Kumar & Ayedee, 2021). Perceived usefulness is characterized as the prospective user's subjective likelihood that using a particular system in an organization would enhance job performance (Alfadda & Mahdi, 2021). TAM consists of two determinants perceived usefulness and perceived ease of use which affect users' attitude toward use and actual use of the system (Alfadda & Mahdi, 2021; Milly, Xun, Meena & Cobbinah, 2021).

The technology acceptance model (TAM) uses the individual's perspective about understanding how technology is adopted (Yoo, 2021). The theory can describe user behavior through various technologies (Davis, Bagozzi & Warshaw, 1989). TAM's objective is to explain the general determinants of technology adoption, describing user behavior across a wide variety of end-user computing technologies and user behavior (Kamble, Gunasekaran & Arha, 2019). TAM's fundamental aim is to provide a framework for tracking internal values, behaviors, and attitudes and the intentions of external influences (Davis, Bagozzi & Warshaw, 1989; Alfadda & Mahdi, 2021). TAM was formulated by defining a small number of fundamental variables suggested by previous research dealing with the cognitive and affective determinants of technology acceptance. Nevertheless, as an instrument for forecasting technology use, TAM has been empirically checked (Larasati & Santosa, 2017; Verma & Sinha, 2018) and is the dominant model in the literature (Davis, 1993). Many studies have been done on technology adoption (Ahuja & Thatcher, 2005; Al-Gahtani & King, 1999; Chang & Cheung, 2001; Cheung, Chang, & Lai, 2000; Igbaria, Guimaraes, & Davis, 1995; Igbaria, Zinatelli, Cragg, & Cavaye, 1997; Jasperson, Carter, & Zmud, 2005; Lewis, Agarwal, & Sambamurthy, 2003; Schepers & Wetzels, 2007; Van der Heijden, 2004; Venkatesh & Davis, 2000), and referred to TAM. Davis (1989) asks: What motivates the acceptance or denial of information technology? Among the many variables are two determinants that are particularly important regarding device usage; the first determinant is that people tend to use an application because they believe it will help them do their jobs better. This variable is known as perceived usefulness (Davis, 1989). The second is when potential users think that a given application is beneficial, but they may find that it is too difficult to use and any benefits are outweighed by the effort to learn it (Davis, 1989). Therefore, in addition to utility, use is theorized as being affected by the ease of use (Talukder, 2014).

The theory aims to explain the determinants of acceptance of the technology (Talukder, 2014). Surbakti, Wang, Indulska and Sadiq (2020) affirm that one such well-tested model of information technology usage is the technology adoption model (TAM). King and He (2006) argue that TAM is now a widely referenced model in information systems because of its comprehensibility and simplicity, but it is not perfect because not all TAM relationships are borne out in different studies due to the various users and systems. So, there is a great discrepancy in the predicted effects. Looking at future technology adoption, Venkatesh and Davis (2000) build TAM2 as another expanded version of the original TAM model and forecast the adoption of information technology (Milly, Xun, Meena & Cobbinah, 2021). TAM2 adds social influences such as voluntariness, subjective norm, and image and cognitive instrumental processes, e.g., demonstrability, job relevance and result, but omitted attitude towards adopting (Venkatesh & Davis, 2000). Figure 3.3 illustrates the Technology Acceptance (TAM) model.

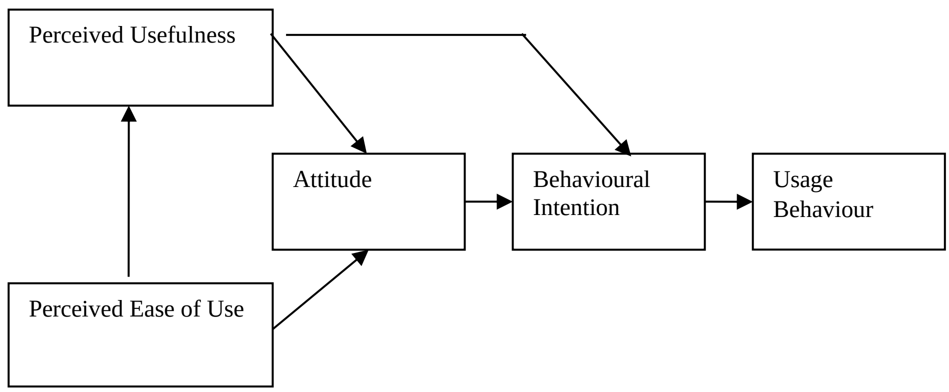


Figure 3. 3 The Technology Acceptance Model (TAM) (Source: Davis, 1989).

Although many technologies acceptance-related studies were conducted using the TAM, their research focused on only attitudinal and behavioral intentions. King and He (2006, p. 740) argue that “TAM has come to be one of the most widely used models in information systems because of its understandability and simplicity”. However, they assert that “it is imperfect, and all TAM relationships are not borne out in all studies; there is a wide variation in the predicted effects in various studies with different types of users and systems” (p. 740). In addition, Yi, Jackson, Park and Probst (2006) state that “TAM should be integrated into a more inclusive model incorporating variables related to both human and social change processes as well as the adoption of innovation” (p. 352). This study’s model is based on technology acceptance-related theories particularly the technology accepted model (TAM) on which the main structure is based on. As TAM is most widely used theory in technology acceptance studies, this study also uses TAM in developing its conceptual framework.

According to Davis, Bagozzi and Warshaw (1989) TAM was formulated by defining a limited number of fundamental variables indicated by previous studies on cognitive issues and computer acceptance affective determinants. It has basically used only 2 determinants, perceived usefulness and ease of use which affect a person’s attitude. Furthermore, “recent studies on IT adoption are generally based on TAM or extensions to it by including one variable, for instance, enjoyment with technology, as one of the predictors" (Chang & Cheung, 2001, p. 2). There are more factors which could affect human behavior. For example, external and demographic variables were not included in the model, but they influence users' attitude to adoption. TAM did not use social influence as it is the least understood factor of technology adoption. Davis (1989) discards subjective norms as negligible and instead identified two central beliefs as the determinants of attitude: perceived usefulness and ease of using a new technology. According to Hu, Chau, Liu Sheng and Tam (1999), TAM is not the best solution for all technological acceptance problems and is constrained. According to them, TAM ignores certain contexts such as culture, gender, and type of information system. Duffy (2012) claims that TAM's chief drawback is that it is a simulation centered on a researcher's point of view and not that of the user. TAM did not consider the effects of external factors such as government or political influence (Duffy, 2012).

As TAM did not include social influence, the model devised for this thesis current employs social factors such as peer influence and social network as determinants affecting users' attitude toward digital technology. Another criticism of TAM is that it did not use political and governmental influence. This study used environmental and political factors that affect employee's adoption of digital systems. Furthermore, the study uses psychological factors such as cultural and religious values that affect the attitude toward digital technology adoption. According to Thompson, Higgins and Howell (1991) the model should not include behavioral intention and attitude should be linked directly to actual behavior. They argued that behavioral intention should be excluded from the model because studies are interested in actual behavior directly. This study looks at actual usage of the system with multiple sets of variables in order to fully examine the extent to which the model can help to understand usage behavior in SMEs.

3.5 Diffusion of Innovations (DOI) Theory

The diffusion of innovations (DOI) theory is concerned with innovativeness, the degree to which a person is relatively early in accepting new practices compared to other people (Haun, Stephan, Wensing, Hartmann, Hoffmann & Friederich, 2020). Relative advantage, compatibility, complexity, trialability, and observability are all factors that influence adoption (Montes de Oca Munguia, Pannell & Llewellyn, 2021). DOI is a theory that seeks to answer the 'how', 'why' and 'what' questions concerning the rate at which innovations are made and disseminating through culture (Folorunso, Vincent, Adekoya & Ogunde, 2010; Arkorful, Barfi & Aboagye, 2021). Kocsis (2020) refined the theory of diffusion innovations (DOI) and based the work on the sociologist Everett Rogers's study in 1962. The adoption of innovations contributed to the growth of the theory of diffusion of innovations (DOI), is dynamic and can be applied in various ways (Arkorful, Barfi & Aboagye, 2021).

Although DOI theory can lead to a better understanding of the organizational-level determinants of technology adoption, it does not consider environmental influences (Ediriweera & Wiewiora, 2021). Adoption refers to a person's decision to do something different than they had previously done. In a social environment, introducing a new concept, product, or behavior such as innovation does not co-occur; it is a mechanism in which specific individuals are more likely to implement innovation than others (Kocsis, 2020). Figure 3.6 illustrates the Diffusion of the Innovations model (Rogers 1995). According to Cozzens and Thakur (2014) the DOI theory is a popular one and led to widely accepted innovation policies in the science and policy development disciplines.

According to Zhang and Nuttall (2011), people who adopt an innovation earlier than others have different characteristics than those who embrace it later; understanding the uniqueness of a target demographic and whether this helps or hinders the acceptance of innovation is critical to promoting innovation. It may employ different strategies to draw the attention of potential innovators. According to Rogers, diffusion occurs when an innovation is shared via specific channels over time among people in different geographical places (Arkorful, Barfi & Aboagye, 2021). Kumar and Kalse (2021) asserted that relative advantage (benefit from the adoption of new technology), compatibility (how much employees are compatible with new technology), complexity (is it complex to utilize a new technology or not), trialability, and observability are the five components of diffusion of innovation theory.

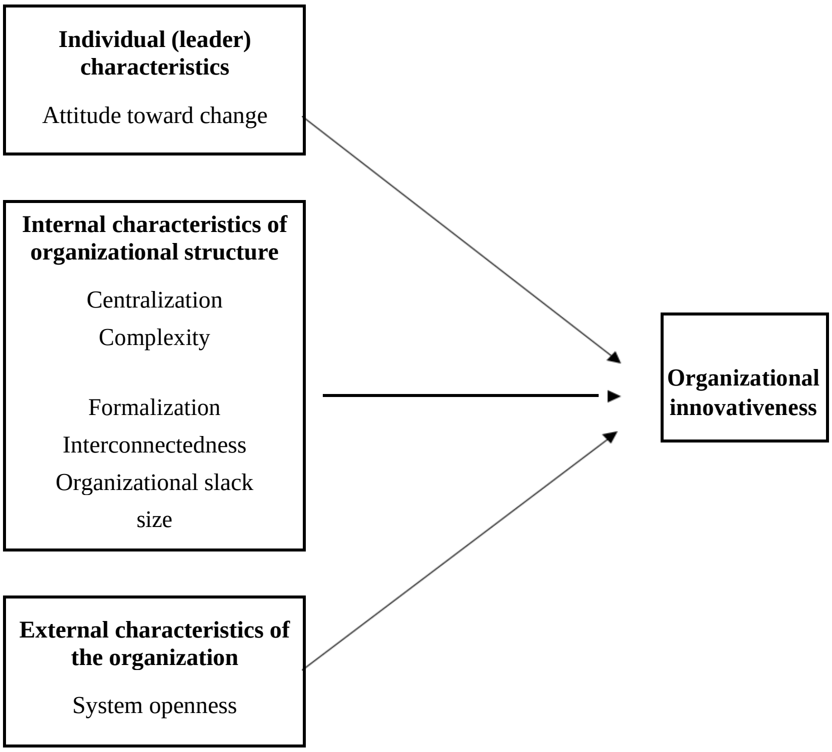


Figure 3.4: Diffusion of innovations theory (Source: Rogers, 1995).

It seems that perceptions of these five characteristics reflect accurate predictors of the acceptance and diffusion of innovations (Rogers, 2003). According to this theory the decision to implement an innovation may affect individuals, organizations, and societies and on the expectations of those in the wide society. Rogers identified five attributes of innovations that comprise the notion of adoption. Firstly, there is the relative benefit, i.e., the degree to which the innovation is viewed as being better than what it replaces through communication processes and channels that permeate the social system. Secondly, compatibility is the point to which innovation is perceived as compatible with current principles, needs and past experiences. Thirdly, complexity is the stage to which innovation is perceived as using and challenging to understand. Fourthly, trialability refers to the stage when an innovation can be tested on a limited basis. Fifthly and lastly, observability is when the consequences of implementing an innovation before it is fully accepted can be seen and understood (Kocsis, 2020). Embracing innovation is a socially rooted strategy. It is a phenomenon characterized by evaluations of the social type that lead to adopters' social image or status (Rogers, 2003). Venkatesh and Davis (2000) explained the possibility of strengthening the explanatory power of the model devised by Davis (1989) and enriching it with three different beliefs of the TAM2 model, namely: 1) voluntary, wherein potential users view the acceptance as compulsory/optional of a technologically dependent innovation; 2) image, capturing the extent to which potential users view their social symbol as adding credibility to a technologically-driven innovation; and 3) result indemonstrability, capturing the degree to which future consumers consider the outcomes of using a particular technologically-driven innovation that can be explained easily to others (Gounaris & Koritos, 2008).

Moore and Benbasat (1991) added more attributes to information technology acceptance. The first is the degree to which an innovation is perceived as being more significant than its predecessor. The second is usability or the degree to which an invention is challenging to use, while the third concerns visibility; this is the degree to which others in the company are using the system. Referring to the fourth, compatibility is the degree to which an innovation is compatible with the current scenario and previous experiences of potential adopters. More than 4,000 papers have been published on DOI in various fields, the vast majority of which were written after Rogers developed his systematic theory (Choe, Kim & Hwang, 2021). Moore and Benbasat (1991) recommended eight general adoption attributes, these being measures for taking and disseminating the adoption of innovations: relative advantage, compatibility, ease of use, demonstrability of outcome, visibility, image, volunteering and trialability (Kocsis, 2020). DOI is essentially a sociological theory, and researchers suggested that the extension and incorporation of technology and innovation must be its key features (Kocsis, 2020). Diffusion of Innovations (DOI) theory is one of the most generally applied theories because it can analyze, estimate, and interpret new technologies' adoption. For this reason, the thesis will adopt DOI theory because it has the ideal attributes for examining SME top managers' perceptions of digital technologies.

3.6 Unified Theory of Acceptance and Use of Technology (UTAUT)

Venkatesh, Morris, Davis and Davis (2003) introduced (UTAUT) and based it on eight prior models and theories relating to the acceptance and use of technology (Francisco & Swanson, 2018; Queiroz & Wamba, 2019; Tamilmani, Rana, Wamba & Dwivedi, 2021; Kumar & Kalse, 2021). According to Dwivedi, Rana, Jeyaraj, Clement and Williams (2019), Venkatesh and others developed the UTAUT model based on an in-depth analysis of eight influential technology adoption theories. They asserted that attitude slightly mediates effort expectancy, performance expectancy, facilitates conditions, and socially influences behavioral intention and directly affects user behavior. Thus, UTAUT emerges as a powerful paradigm that explains the technology's acceptance (Scherer, Siddiq & Tondeur, 2019). Figure 3.7 illustrates the UTAUT model.

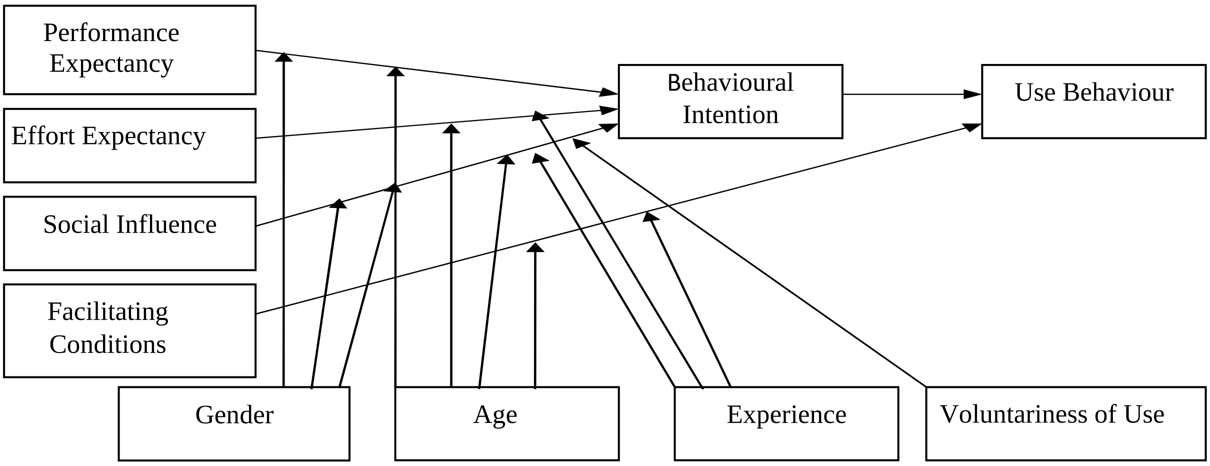


Figure 3.5. The Unified Theory of Acceptance and Use of Technology (UTAUT) (Source: Venkatesh, Morris, Davis & Davis, 2003).

Four aspects of the user's acceptance and behavior are covered in this theory (performance expectancy, effort expectancy, facilitating conditions, and social influence), which are thought to be fundamental determinants of users' behavioral intention, and information technology use. (Venkatesh et al., 2003). Individual moderating variables such as gender, age, and experience, as well as how voluntarily people use technology exert an impact on the four components or constructions that lead to the acceptance of digital technologies in SMEs (Kumar & Kalse, 2021). Accordign to Talukder (2014), UTAUT theory postulates that success expectancy, effort expectancy and social impact decide the behavioral intention to use technology, facilitating situations that influence usage actions. In the model, moderating variables such as gender, age, experience, and willingness serve to help analyze the relationship between the independent variables and the intention to manipulate behavior.

On the other hand, the applicability and generalizability of UTAUT have been criticized because it refers mainly to organizational and academic settings (Oliveira, Thomas, Baptista &

Campos, 2016). Yet when compared to other technology adoption models, UTAUT appears to be more comprehensive as it identifies four main determinants of users' intentions and the actual use of technology: expectation of effort, social effect, performance, and facilitation of conditions (Venkatesh, Morris, Davis & Davis, 2003). The results of these determinants are presumed to be moderated by the gender, age, experience, and willingness of respondents (Williams, Rana & Dwivedi, 2015). The UTAUT model has been extensively applied and tested for predicting system usage and making technology adoption and usage-related decisions in a variety of fields, including interactive whiteboards, near-field communication technology, mobile health, home telehealth services, and ERP software acceptance (Chao, 2019). Many studies prefer the UTAUT model when investigating the uptake of cloud computing in SMEs, and social influence is now considered to be a determinant for adoption (Kumar & Kalse, 2021). Although the UTAUT model has enjoyed widespread acceptance, there are concerns about its ability to explain individual technology acceptance. As a result, the UTAUT model has been refined or changed (Chao, 2019). This study constructs an enhanced proposed model by adopting the UTAUT model with modifications to measure the adoption and use of digital technologies in Jordanian SMEs.

3.7 Technology Organization Environment (TOE) framework

Tornatzky and Fleischer introduced the technological, organizational, and environmental (TOE) model in (1990) based on the contingency theory of Fred Fiedler, which categorizes the common factors that influence the adoption of technology and the processes of technological innovation (Baker, 2012; Pumplun, Fecho, Wahl-Islam & Buxmann, 2021; Park & Kim, 2021; Kumar & Kalse, 2021). TOE examines the adoption of several IS/IT products and services at the firm level (Shahzad, Xiu, Khan, Shahbaz, Riaz & Abbas, 2020). Several theories have been devised for technology adoption and researching its usage. The TOE model has taken variables or components from previous theories and models and combined them (Kumar & Kalse, 2021). TOE is a theoretical model with roughly characteristic technological innovation adoption features (Rouhizadeh, Saberi & Sarkis, 2021). The TOE framework provides an appropriate starting point for studying digital information technologies (IDT) (Khayer, Talukder, Bao & Hossain, 2020). The technological context describes internal and external technologies relevant to businesses (Khayer, Talukder, Bao & Hossain, 2020); Ghobakhloo & Ching, 2019), their equipment internal and practices (Starbuck, 1976) and the set of externally based technologies that are available to the company (Hage, 1980).

While the organizational context refers to descriptive measures such as scope, scale, and management structure, a corporation is usually a big multinational or national business that has large-scale operations, markets, rivals, and relationships with governments (Tornatzky & Fleischer, 1990). Tornatzky and Fleischer (1990) claimed that technological innovation processes helped refine the TOE framework and there are three elements that influence the mechanism through which technological innovations emerge (Oliveira & Martins, 2011). Wong, Leong, Hew, Tan and Ooi (2020) stated that the TOE model has a clear theoretical foundation, consistent empirical support and the potential to be applied to Information Systems innovation. Xu, Zhu and Gibbs (2004) confirmed that the TOE model has a clear theoretical foundation, much empirical support, and other innovation features which can be implemented (see also Jeyaraj, Rottman and Lacity; 2006; Fichman, 2000).

Bradford, Earp and Grabski (2014) state that the technological context might involve equipment types and processes, while the organizational context refers to the company's characteristics, such as the degree of formalization, management structure, human resources management and how employees and their sections are linked. In the external task environment, the industry's size and structure, the company's competitors, the macroeconomic background, and the regulatory climate, guide our understanding of the information system (Bradford, Earp & Grabski, 2014). Arnold, Kilian, Thillosen and Zimmer (2018) researched the determinants of TOE-based Industry 4.0, finding that the determinants driving it are relative competitive advantage, management support, and environmental instability. They did this by looking at the specifics of embracing current information technology from the technological, organizational, and environmental (TOE) perspectives (Wong, Leong, Hew, Tan & Ooi, 2020). The environmental context poses both innovation opportunities and constraints, while the TOE model makes it possible for Rogers' theory of innovation diffusion to explain intra-company innovation diffusion (Oliveira & Martins, 2011). The TOE model is consistent with the Rogers (2003) theory of diffusion of innovations (DOI) since it focuses on the organization’s internal and external factors as well as technical characteristics that drive the diffusion of new technologies (Khayer, Talukder, Bao & Hossain, 2020). Figure 3.8 illustrates the (TOE) model as devised by Tornatzky and Fleischer (1990).

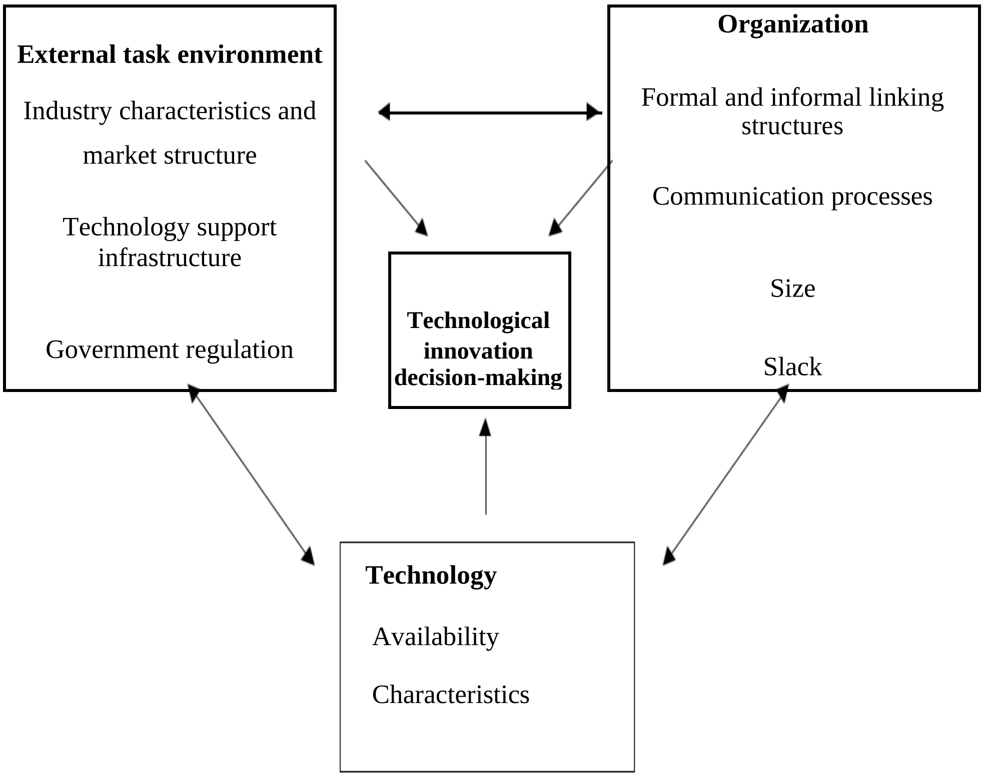


Figure 3.6: Technology, organization, and environment framework (Source: Tornatzky & Fleischer, 1990).

Determinants can vary from study to study when using the three contexts (Oliveira & Martins, 2011). TOE's framework identifies a holistic strategy that could be merged with other ICT frameworks (Alkhalil, Sahandi & John, 2017). Many studies have applied the TOE model to understand the adoption of technological innovation with reference to organizational, and environmental contexts (Hossain & Quaddus, 2011; Shahzad, Xiu, Khan, Shahbaz, Riaz & Abbas, 2020). The TOE concept is consistent with Rogers' (1989) dissemination of innovation theory. It focuses on the organization's internal and external characteristics and technological characteristics in studying drivers that disseminate new technology (Ghobakhloo & Ching, 2019). Several studies have used the TOE framework for the analysis of digital information technologies adoption domains, electronic funds transfer, exchange of electronic data, ERP, and open systems, etc. The TOE framework has a sound theoretical basis that can be applied to information system domains (Bradford, Earp & Grabski, 2014).

The TOE model echoes the Model of Technology Acceptance (TAM) in that user habits are among the determinants of digital technologies acceptance behaviors (Ghobakhloo & Ching, 2019; Dincă, Dima & Rozsa, 2019). Furthermore, the TOE model considers multidimensional aspects of an entity when assessing technology adoption and diffusion; compared to other adoption frameworks such as the Technology Acceptance Model, TOE seems to be better at explaining the issues than TAM. According to Putra and Santoso (2020), several scholars indicated that it was not wise to use the TOE model on its own to create a theoretical causal relationship. TOE does not restrict the industry or firm size and it gives the user a complete view of technology adoption, including anticipated difficulties, adoption decision considerations, and how IT can improve organizational capabilities (Shahzad, Xiu, Khan, Shahbaz, Riaz & Abbas, 2020). The current study uses the TOE framework to explain various technological, organizational, and environmental determinants on the attitudes and intentions to use digital technologies in Jordan.

3.8 Electronic data interchange (EDI)

Studies published on small businesses have concentrated on unique kinds of technology. A significant example of electronic data interchange (EDI) is that it parallels the internet, given that EDI provides consumers with an electronic connection (Kuan & Chau 2001; Masudin, Aprilia, Nugraha, & Restuputri, 2021; Klapita, 2021). Figure 3.11 illustrates the (EDI) Model (Iacovou, Benbasat & Dexter, 1995). EDI is an evolving standardized inter-organizational information system (Wang & Seidmann, 1995). Combining information and telecommunications technology has enabled a wide range of telematics systems, including those utilized in transportation. Consequently, telematics systems constitute important technological advances whose functionality is ensured by the electronic exchange of EDI data (Kopczewski, Grobelny & Pucienniczak, 2020). The following three factors that affect small businesses' adoption of EDI were established by Iacovou, Benbasat and Dexter, 1995): (i) the organization's perceived benefits of EDI, including direct ones such as operating savings and indirect benefits, like improved business processes; (ii) financial capital and technical preparation for organizational readiness; and (iii) external demands on the organization to incorporate the technology (from competitors and imposed by trading partners).

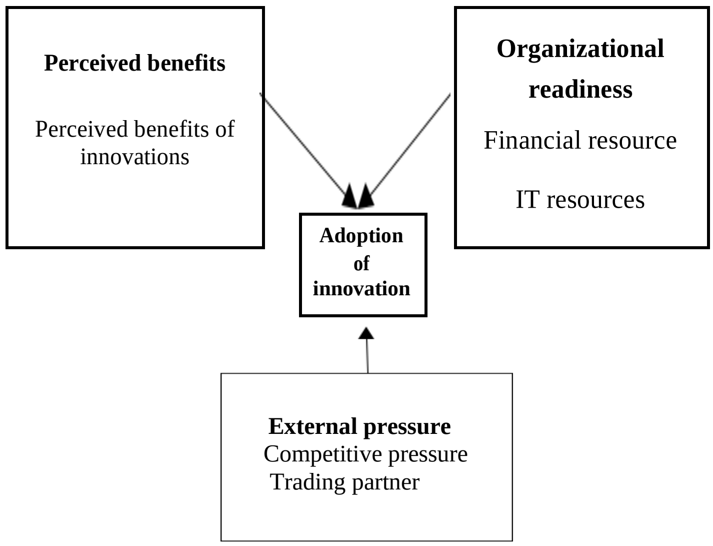


Figure 3.7: Electronic data interchange EDI model of Iacovou et al. (1995)

In the work of Kaplan, Johnson, Pearce and George (1997) there is some evidence that these factors may contribute to SMEs' adoption of the Internet, as it provides several real advantages, including international and immediate reach. The benefits of using the Internet in SMEs for marketing/promoting, advertising, online selling, communication, and collaboration are documented (Mehrtens, Cragg & Mills, 2001). The proper operation of current supply chains demands speedy and instant communication wherein all aspects of business are integrated, which can be accomplished through EDI (Kopczewski, Grobelny & Pucienniczak, 2020). It is vital to use the most up-to-date ICT technology to connect many businesses and institutions nationally and globally (Kopczewski, Grobelny, & Pucienniczak, 2020). All processes in a transportation company's relationships with customers, such as orders, delivery notes or invoices, goods transportation itself, logistics, and other processes are critical parts of a supply-customer chain. They can be significantly simplified and accelerated through EDI and a suitable interface for application programming (Klapita, 2021). The Internet provides an opportunity for a company to research industry and business trends, and what competitors are doing and the pressures that exist (Cronin, Overfelt, Fouchereaux, Manzvanzvike, Cha & Sona, 1994; Mehrtens, Cragg & Mills, 2001).

Kopczewski, Grobelny, and Pucienniczak (2020) contend there are four stages of success related to the use of EDI technology: 1) technical success, which involves a high utilization of technical capability and is associated with much less non-production downtime; 2) direct operational success in terms of lowering labor costs and other overheads; 3) indirect operational success, evident in reduced order processing times, improved product quality, and better process flexibility; and 4) strategic success, measured by company's market competitiveness and improved profitability. A multiple case study research program has described the EDI adoption model whereby the perceived advantages, organizational readiness, and external pressures can be explained by integrating with the TOE model (Kuan & Chau, 2001). Businesses now reap great benefits by switching from paper-based to electronic/online business documentation which is cheaper, faster and more reliable for establishing stronger relationships with business partners (Klapita, 2021). Yet certain elements of the TOE model concerning the technology, organizational context with the predictors of perceived advantages, organizational readiness, and external pressure have not been compared to the EDI adoption model (Baker, 2012). Electronic Data Exchange (EDI) literature has shown that the opportunity to share information increases operational efficiency, including reduced cycle time and better quality (Clemons, Reddi & Row, 1994).

3.9 De Lone and McLean's information systems success model

DeLone and McLean (1992) created the information system (IS) success model, which seeks to explain busers' satisfaction through the concepts of system quality, information quality and user behavior (Jewer & Compeau, 2022). It aims to generate comprehensive knowledge about IS success by identifying and explaining the relationships between the most critical elements (DeLone & McLean, 2003; Talukder, 2014; Sabeh, Husin, Kee, Baharudin & Abdullah, 2021; Jewer & Compeau, 2022). DeLone and McLean introduced a "taxonomy" and "interactive" model to "conceptualize" and "operationalize" the success of information systems (Wu, 2007). The Information System (IS) success model comprised six linked elements: system quality, information quality, use, user satisfaction, individual impact, and organizational impact (Sabeh, Husin, Kee, Baharudin & Abdullah, 2021; Jewer & Compeau, 2022). Information Systems (IS) are used by businesses to support their operations and facilitate growth (Jewer & Compeau, 2022). However, because achieving the desired outcomes of these systems can be difficult, there is a continuing interest in determining the aspects that contribute to their success (Jewer & Compeau, 2022). A new information system's success can be measured in terms of the project (e.g., on-time, on the budget), user response (e.g., contentment or resistance) to the system such as high-quality system that provides expected benefits (Wilson & Howcroft, 2002). DeLone and McLean define the system's quality as its features and measurable technological performance (Sabeh, Husin, Kee, Baharudin & Abdullah, 2021). Figure 3.12 illustrates the DeLone and McLean model (1992).

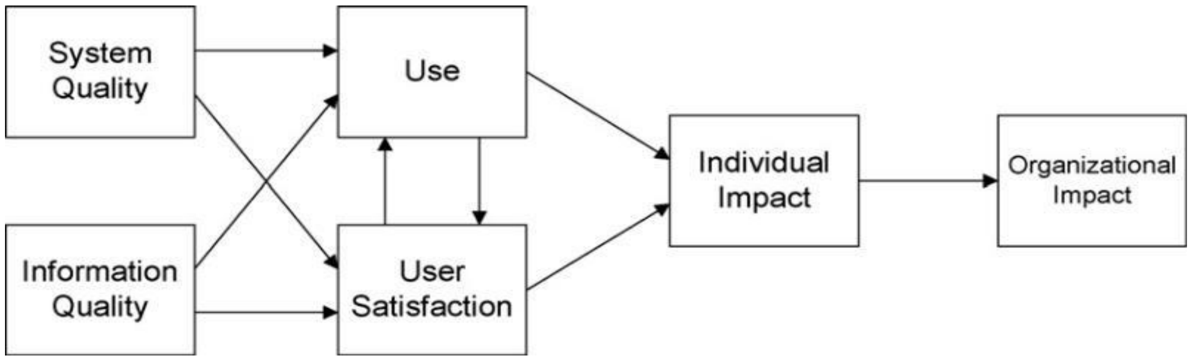


Figure 3.8: DeLone and McLean's model (1992).

The quality of information indicates the features of the relevant product and success calculation. In terms of the efficacy of an information system, user satisfaction, individual and organizational aspects shape the performance and the subsequent effect on the user (Lin, 2008; Sabeh, Husin, Kee, Baharudin & Abdullah, 2021). This model suggests that when an IS system and its features can be observed and in terms of quality, users are either pleased or unhappy with it (Sabeh, Husin, Kee, Baharudin & Abdullah, 2021; Talukder, 2014). The system's use affects the individual's work output and productivity (Wu, 2007). DeLone and McLean (2004) stated that the model has six connected dimensions, and a causal relationship exists between them: 1) system quality, 2) information quality, 3) user satisfaction, 4) IS use, 5) individual impact, and 6) organizational impact (see also Lin, 2008). The model suggests that when an information system is developed, it incorporates significant features and characteristics that exhibit varying degrees of system quality and information quality (Talukder, 2014).

The use of the system by individual workers will collectively affect the firm (DeLone & McLean, 1992). DeLone and McLean (2003) explained how the model worked by stressing the value of user satisfaction in terms of the method and user optimism; the model explains the factors that influence a company's ability to implement the technology. It appeared that the DeLone and McLean model was ambiguous in its original form because the process models and variances were combined in the same setting (Seddon, 1997). Researchers have done more research to revise or extend the DeLone and McLean model according to Seddon's suggestions (Sabeh, Husin, Kee, Baharudin & Abdullah, 2021). The proposed model devised for this study does not look at the path of technology adoption; instead, it emphasizes how various internal and external environment determinants interact to form perceptions of technology and its subsequent adoption and the assumed benefits. DeLone and McLean's model aims to provide a comprehensive rationale of IS success by identifying and explaining the relationships between the most critical determinants of success (Jewer & Compeau, 2022).

3.10 Combined TAM and TPB Model

Taylor and Todd (1995) create a hybrid model by combining the TPB predictors with the perceived usefulness and ease of use constructs derived from the TAM model (Ning, Yan, Xu, Li & Li, 2021). Since the model's framework is a decomposed one, this model is often called the Decomposed Theory of Expected Conduct. It includes perceived usefulness, perceived ease of use and compatibility. According to Taylor and Todd (1995), TAM is still an easy and quick way to predict users' true technology intentions. However, it ignores social and cognitive elements like the subjective norm and perceived behavioral control, which are critical in understanding technology acceptance from a psychological standpoint. Lu, Huang and Lo (2010) used TAM and TPB to examine the factors that influenced taxpayers' willingness to use an online tax filing system. According to their findings, users formed a more favorable opinion of the new system when they viewed the online tax reporting method as practical and straightforward (Choe, Kim & Hwang, 2021).

TAM and TPB's combined model would help anticipate consumers' intentions regarding the use of digital technologies like ‘drone food delivery services’ more accurately (Choe, Kim & Hwang, 2021). Yang and Su (2017) used the TAM and TPB to investigate how students reacted to IT and new teaching methods, and they discovered that attitude was an essential element influencing students' behavioral intentions. Furthermore, learners' intentions to abide by a new teaching approach were influenced by subjective norm and behavioral control, which were significant variables. As a result, C-TAM-TPB, which includes the benefits of both TAM and TPB, emerges as the best model for this study since TAM considers elements from a technological standpoint, while TPB considers factors connected to user characteristics (Ning, Yan, Xu, Li & Li, 2021). Peer influence and superior influence are included in the normative belief structure and self-efficacy; resource-facilitating conditions and technology facilitating conditions control belief structure (Li, 2010). Figure 3.11 illustrates the Combined TAM and TPB model.

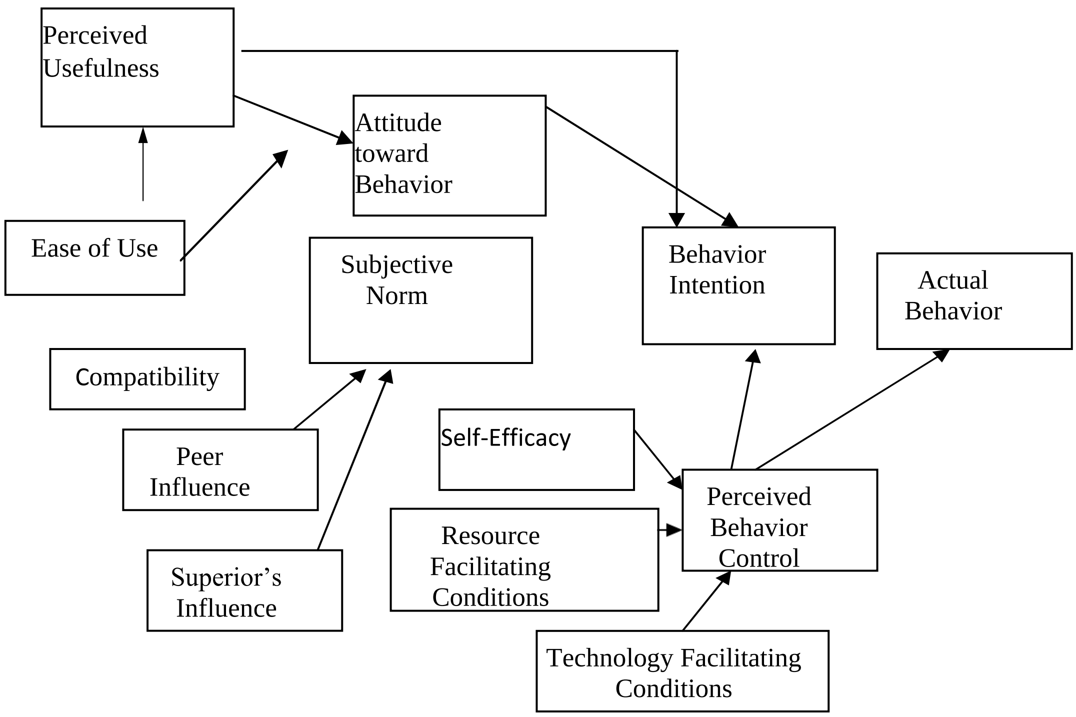


Figure 3.9: Combined TAM and TPB model (Source: Taylor & Todd, 1995).

3.11 The Motivation Theory

Research has looked at certain motivational viewpoints for the adoption of information technology, arguing that both hedonic and utilitarian criteria drive people's decisions about IT (Luo, Chea & Chen, 2011). Davis, Bagozzi and Warshaw (1992) applied the motivation model to research how information technology was implemented, suggesting that individuals' conduct is based on external and internal motivations. Wu, Gu, Gu, and You (2021) write that individual motivation arises from a demand; people are willing to put in long hours to meet this demand. Similarly, motivation and trust are inextricably intertwined—users' reciprocal motivation in virtual communities. People's attitudes are influenced by their motivation (Wu, Gu, Gu & You, 2021). External motivation is described as the belief that users want an activity "because it is perceived to be instrumental in achieving valued results that are different from the activity itself, such as improved job performance, pay, or promotions" (Davis, Bagozzi & Warshaw, 1992). Examples of external motivation are perceived ease of use, perceived usefulness, and subjective norms. At the same time, substantial motivation refers to the experiences of enjoyment and satisfaction with behavioral success (Vallerand, 1997). Users want to conduct an operation or action "for no apparent reinforcement other than the activity per se performance process" Davis, Bagozzi & Warshaw, 1992). Examples of substantial motivation are computer playfulness and enjoyment (Li, 2010). Consequently, it is not only extrinsic motives but also intrinsic motives (i.e., perceived usefulness and perceived enjoyment) that drive people. Several studies have confirmed that essential predictors of behavioral use are both intrinsic and extrinsic motivations (Luo, Chea & Chen, 2011).

3.12 The Model of PC Utilization

Triandis (1977) claimed that the theory of attitudes and behavior is different from TRA and TPB. There is a distinction between cognitive and affective elements of attitudes (Triandis, 1980). According to Thompson, Higgins and Howell (1991), beliefs belong to cognitive component of attitudes and behavior are determined by what individuals want to do (attitudes), social norms in terms of what they think they should do, and habits, which is what they usually do, and the expected outcomes of their behavior. Thompson, Higgins and Howell (1991) refined the Triandis model to predict PC utilization behavior. Figure 3.13 illustrates the PC Utilization model.

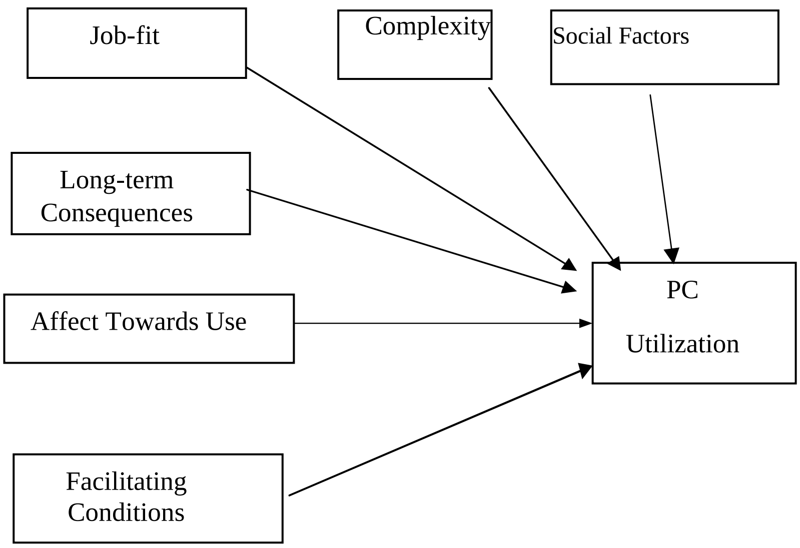


Figure 3.10 The PC Utilization model (Source: Thompson et al., 1991).

The primary constructs and their definitions in the model are documented below:

- Job-Fit: the degree to which an individual believes that using technology can improve his or her job performance.
- Complexity: refers to the degree to which an innovation is perceived such as relatively hard to understand and use.
- Long-term consequences: outcomes that have a pay off in the future.
- Affect Towards Use: pointing to feelings of joy, elation, or happiness, or depression, disgust, displeasure, or hatred associated with a specific act.
- Social Factors: individual internalization of the reference group's subjective culture and specific interpersonal agreements that the person has made with others in particular social situations.
- Facilitating Conditions: support for PC users may be one kind of facilitating condition that can guide system utilization.

3.13 The Social Cognitive Theory (SCT)

Social Cognitive Theory (SCT) describes how individual behavior and experiences, other people's attitudes, and environmental forces all influence personal habits (Wu, Gu, Gu & You, 2021). Pinch and Bijker (1987) were the first to undertake work on SCT. They identified four key components. The initial component is interpretive flexibility which allows for a better understanding of technology design as an open process producing various outcomes depending on the social context of development. The second component refers to the relevant social group. Closure and stabilization constitute the third component of the SCT framework, while the fourth is the socio-cultural and political context in which artefact development occurs. These scenarios involve all members of a particular social community looking at a specific artefact in the same way and according to it the same meaning (Pinch & Bijker, 1987).

On the other hand, Social Cognitive Theory (Bandura, 1989) asserts that environmental and personal factors (in the form of cognitive variables) are the key influential factors. This theory includes two key concepts: self-efficacy and trust. Self-efficacy indicates a person's perception of competence, making it a significant individual aspect (Wu, Gu, Gu & You, 2021). Moreover, behaviors are mutually defined. Cognitive skills influence technology, and cognitive expectations are often shaped by successful encounters with technology, so the idea of self-efficacy is prevalent in SCT (Compeau, Higgins & Huff, 1999). Self-efficacy is described as evaluating one's ability to use technology to execute a specific task (Compeau & Higgins, 1995). Outcome perceptions, including personal and performance-related ones, are essential cognitive variables that affect users' actions (Compeau & Higgins 1995). Personal-related outcome expectations are concerned with the esteem and sense of achievement that individuals have. SCT claims that self-efficacy affects the perceptions of both personal and performance-related outcomes (Compeau & Higgins, 1995). Two influential variables are attraction and fear. Affect refers to the liking of a person for a specific action (e.g., computer use), while anxiety refers to a person's nervous or emotional reaction in performing a behavior like using a computer (Li, 2010). Pinch and Bijker's work does not put enough focus on the socio-cultural and political contexts, such as the contextual conditions of group interactions and their relationships, rules, and factors that lead to power differences. Hence, Social Cognitive Theory (SCT) describes how individual behaviors and experiences influence other people's attitudes (Wu, Gu, Gu & You, 2021). The proposed model in this study will incorporate a socio-cultural context, one that is made up of several elements.

3.14 Technology Readiness Index (TRI)

The Technology Readiness Index (TRI) was proposed by Parasuraman in 2000. He developed TRI to explain people's inclination to adopt a new technology in their personal lives and at work (Syamfithriani, Mirantika, Yusuf & Kurniadi, 2021). The TRI model serves to assess a person's general attitudes to technology (Syamfithriani, Mirantika, Yusuf & Kurniadi, 2021). Moreover, TRI is an overall state of mind arising from a gestalt of mental enablers and inhibitors that collectively decide an individual's predisposition to use new technologies (Kamble, Gunasekaran & Arha, 2019). TRI tests people's general beliefs regarding technology and consists of four sub-dimensions (optimism, innovation, anxiety and insecurity). Optimism can indicate a positive perception of technology and functions as a belief that performance, better control, and versatility can be brought about, while innovation refers to consumers' inclination to be technology leaders (Kamble, Gunasekaran & Arha, 2019). Discomfort reflects the feeling of loss of control and a sense of insecurity when using technology. Finally, insecurity relates to technology worries or mistrust and skepticism about its ability; innovation and optimism are known as technology motivators, while discomfort, and insecurity function as inhibitors (Kamble, Gunasekaran & Arha, 2019; Larasati & Santosa, 2017).

3.15 Resource-based View (RBV)

In the mid-1990s, the Resource-Based View RBV appeared in the IT literature (Yang, Xun & He, 2015), and over the last three decades, it has been very influential in explaining how organizations achieve and maintain a competitive advantage (Barney, 1991; Zahra, 2021). When businesses can adopt value-creating strategies that are very different from rival firms and they adapt better to industry conditions (Eisenhardt & Martin, 2000), RBV makes it possible to understand company-specific drivers of SMEs' performance output (Zulu-Chisanga, Chabala & Mandawa-Bray, 2020). RBV considers organizations to be packages of resources and skills that help them establish their business strategy (Ruiz-Alba, Guesalaga, Ayestarán & Mediano, 2019; Soliman & Karia, 2021).

Eller, Alford, Kallmünzer and Peters (2020) argue that RBV resources and skills must be valuable, rare, not able to be imitated, and non-substitutable (VRIN) to achieve a sustainable competitive advantage (Barney & Hesterly, 2010; Barney, Wright & Ketchen, 2001). A company's resources and abilities comprise the fundamental sources of competitive advantage and better financial performance (Barney, 1991; Barney & Hesterly, 2012; Zulu-Chisanga, Chabala & Mandawa-Bray, 2020). According to Eller, Alford, Kallmünzer and Peters (2020) the resource-based view offers a valuable lens for assessing SMEs' attitudes to digitalization, and the relationships and how they deploy Information Systems for dealing with customers (Lonial & Carter, 2015; Barney & Arikan, 2001).

An organization must have the right policies and processes in place to use its resources to their maximum capacity (Ruiz-Alba, Guesalaga, Eyestrain & Mediano, 2019). The Resource-Based View (RBV) analyses and interprets organizations' internal resources and emphasizes capabilities in formulating a plan to gain sustainable competitive advantage (Madhani, 2010), and IT plays a role here (Mubarak et al., 2019; Shahbaz, Chandio, Oad, Ahmed & Ullah, 2018). The marketing literature indicates that enhanced information capabilities significantly guide consumers' satisfaction, purchase experiences, and loyalty (Alba, Lynch, Weitz, Janiszewski, Lutz, Sawyer & Wood, 1997). It is noted by Lado, Boyd, Wright and Kroll (2006) stated that critics view RBV as having its own contradictions. The RBV view contends that businesses must accumulate hidden assets over time and mobilize them in conjunction with technology or company values to gain and retain a competitive advantage especially internationally (Musteen, Ahsan & Park, 2017). RBV is suitable for assessing SMEs, exploring the antecedents of their external service activities. Accordingly, to investigate why SMEs prefer to do business offshore means looking at services or activities can range from low-cost access but leading to better market value and production outcomes (Bunyaratavej, Doh, Hahn, Lewin & Massini, 2011). To date, most discussion has focused on demonstrating the value and relevance of RBV for entrepreneurial businesses (Zahra, 2021). As a result, the RBV approach has been widely used by established businesses to determine which resources will help create a competitive edge, for example, collaborative ties such as technology-based joint ventures (Zahar, 2021; He, Brouthers & Filatotchev, 2013; Wernerfelt, 2013).

3.16 Knowledge-based View (KBV)

The Knowledge-based view (KBV) theory is an extension of RBV (Barney, 1991). Experts in this field have taken the lead in establishing the firm's knowledge-based perspective (KBV) and applying it to a global context (Grant & Phene, 2021). In terms of theory, the nature and qualities of knowledge serve as a common ground for various management study areas, including organizational learning, technology and innovation, information systems, evolutionary and resource-based firm theories, and decision science (Grant & Phene, 2021). Conner (1991) considers expertise the most strategically relevant of a firm's resources (Kogut & Zander, 1992). Nonaka (1994) clarified that organizational knowledge is conveyed through various entities, including workplace culture, identity, policies, habits, records, processes, and personnel, given that knowledge-based resources are heterogeneous and difficult to imitate and transfer. The main determinants of sustained competitive advantage are the knowledge base and capabilities within companies (Barney, 1991). Alavi and Leidner (2001) have argued that IT can play an essential role in a company's business practices in that information systems synthesize, enhance, and speed up large-scale intra- and inter-company knowledge management. Three types of IT-based resources have been suggested and empirically tested by Bharadwaj (2000), leading to superior company performance: (1) physical IT infrastructure, including physical IT assets and systems; (2) human IT capital, IT workers and managers; and (3) intangible IT-enabled resources, including customer focus, knowledge-based assets, and synergies (see also Li, Merenda & Venkatachalam, 2009).

3.17 Institutional theory

Institutional theory dates back to the work done by Meyer and Rowan (1977). This is a theory in which institutions carry out the "means" of technology acceptance, which are procedurally specified by management or owners and lead to the 'way of doing things' (Crank, 2003). Institutional theory stresses that institutional environments influence organizational structure and behavior (Olivera & Martin, 2011; Guerreiro, Lima Rodrigues & Craig, 2021). Institutions are conceived as socially developed, routine-reproduced program or functional structures, functioning as restrictive environments where certain routines have to be followed (Jepperson, 1991). According to institutional theory, decisions are not motivated solely by performance objectives but by social and cultural considerations and credibility issues. Also, this theory considers themes of stability, uniformity, and isomorphism, and here IT evolves as the subject of requirements which can be ambiguous, fragmented, and complex in terms of the effect on organizational structures/processes (Guerreiro, Lima Rodrigues & Craig, 2021).

The theory suggests that businesses become more alike due to isomorphic forces and pressures because they want to garner legitimacy (Dimaggio & Powell, 1983). As economic and consumer demands drive them to mimic market leaders or their rivals, businesses in the same sector appear to offer the same services and goods/services. Businesses are likely to be persuaded to accept and use e-commerce as an external isomorphic pressure because trading partners, consumers, and governments now embrace e-commerce (Olivera & Martin, 2011). Several studies have taken an institutional approach to e-commerce or EDI diffusion and assimilation (Teo, Wei & Benbasat, 2003). Mimetic, coercive, and normative institutional pressures influence organizations' predisposition to operate with an IT-based inter-organizational system (Teo, Wei & Benbasat, 2003; Guerreiro, Lima Rodrigues & Craig, 2021). Olivera and Martin (2011) write that mimetic pressures are observed when businesses implement a practice or innovation that imitates what rivals do. Coercive pressures are a series of formal or informal forces exerted by other organizations based on the former.

Normative pressures stem from dyadic relationships where businesses share specific knowledge, laws, and norms (Olivera & Martin, 2011). Sharing these standards among members of a network across relational networks promotes consensus, which enhances the strength of these standards and their potential impact on organizational behavior and those of the staff (Powell & DiMaggio 1991). The TOE model is coupled with institutional theory in some studies (Gibbs & Kraemer 2004; Li, 2008; Soares-Aguiar & Palma-Dos-Reis, 2008). DiMaggio and Powell (1983) suggested that firms are embedded in institutional networks, and they called for an increased emphasis on recognizing institutional pressures when examining IT innovation adoption. Isomorphism is embedded in institutional theory and useful when applying the information system as a social phenomenon (Ahmadi, Ibrahim & Nilashi, 2015). "Isomorphism" is imposed at the organizational level where institutional pressure is mimetic, oppressive, and normative. Such stresses lead to business processes that are assimilative in character (Jensen, Kjærgaard & Svejvig, 2009). Institutional theory applies external pressure which is generated by rivals, and this echoes the claims of the TOE model (Olivera & Martin, 2011).

3.18 Justification for using technology adoption models and theories

Throughout the business world, technological advances play a critical role and disseminate knowledge and data in new ways, but technology is of no use unless and until it is accepted and used (Kamble, Gunasekaran & Arha, 2019). Although adoption is applied at the individual level, technology adoption will contribute to diffusion (Sharma & Mishra, 2014). Understanding the adoption of technology is, therefore, of paramount importance and it can be defined as a desire within a community of people who want to benefit from it (Venkatesh, Thong & Xu, 2012). Dincă, Dima and Rozsa (2019) assert that most technology adoption theories/models view and forecast the options based on components connected to the technology itself or consumers' input and assumptions. Nevertheless, technology-related concerns are not the only factors that decide the acceptance of technologies. Other influences are crucial for the preference for a particular innovation and can stem from an environmental and organizational nature (Dincă, Dima & Rozsa, 2019).

It seems technology acceptance theories emphasize that IT is adopted in individual, community and country contexts (Chege, Wang & Suntu, 2020). Several studies have shown that it has developed as a much more complex mechanism involving users' attitudes based on their personality dimensions, social impact, confidence, and various facilitation features (Kamble, Gunasekaran & Arha, 2019). Musawa and Wahab (2012) believed that a voluntary decision was the first step in adopting or operating any information technology at an individual or organizational level. All strategic decisions are positively affected by owners or executives in SMEs. A representation of the owners or CEOs' characteristics is then seen in the decision-making process (Khayer, Talukder, Bao & Hossain, 2020). To explore the adoption of digital technologies at the corporate level, many research models and theories have been established. Consequently, the theories and models used in this research include the following (and these have already been covered earlier in the chapter):

- Technology acceptance model (TAM) by Davis (1989)
- Theory of reasoned action (TRA) by Ajzen and Fishbein (1980).
- Diffusion of innovations (DOI) by Rogers (1995).
- The Social Cognitive Theory (SCT)
- Technology–Organization–Environment (TOE) by Tornatzky and Fleischer (1990).
- Unified theory of acceptance and use of technology (UTAUT) by Venkatesh, Morris, Davis and Davis (2003).

According to Awa, Uko, and Ukoha (2017), at the corporatre level business strategies are directly affected by decision-makers' perceptive idiosyncrasies and their feelings about the utility of a given technology, which drive motivation and attitude. Sometimes, company-level technology adoption decisions, particularly in SMEs, are influenced by decision-makers' excitement and possibilities of business growth, the conviction of owners' and managers' motivations (Awa, Ojiabo & Emecheta, 2015). Nevertheless, in the literature, it seldom adopted socio-cultural characteristics (e.g., peer support, social network, religious beliefs) and while the TOE framework acknowledges decision-makers' understanding as a factor underlining the organizational context, considering them as an independent context rather than a construct is likely to boost predictability and the explanatory capacity of, for example, the TOE model (Awa, Uko & Ukoha, 2017).

Government laws and regulations on the utilization of digital technology are significant for enterprises and are considered significant challenges at the corporate level. Baker (2012) asserts that researchers have used slightly different factors for the technological, organizational, and environmental contexts in most empirical studies that assess the TOE system. They have also chosen different kinds of innovative technologies. Similarly, diverse national/cultural backgrounds and various industries may lead to different kinds of variables, and this certainly the case when assessing digital technologies in Jordanian SMEs. The current literature on information systems verifies the positive outcomes of digital technology adoption, but researchers overly emphasized the initial adoption decision only (Khayer, Talukder, Bao & Hossain, 2020). Many studies have referred to the TOE framework when examining digital technologies at the SME level, for instance: E-Business (Putra & Santoso, 2020), Smart Factory adoption (Won & Park, 2020), Cloud computer adoption (Shahzad, Xiu, Khan, Shahbaz, Riaz & Abbas, 2020) and Big data analytics (Maroufkhani, Tseng, Iranmanesh, Ismail & Khalid, 2020). In Table 3.1 below studies done on digital technologies at the SME level are summarized.

Table 3.1: Studies on digital technologies at the SME level.

Adoption area	**Authors**	**Variables Analyzed**	**Geographical and Organizational Context**
Smart factory adoption	(Won and Park, 2020)	• Technology: perceived benefit (BSC performance, Process effectiveness) • Organization: organizational support, information capability, IT financial resource • Environment: External pressure (Business environment government policy)	3700 SMEs in South Korea
Cloud computer adoption	(Shahzad et al., 2020)	• Technology: relative advantage, complexity, compatibility, Cost reduction • •Organization: financial slacks, top management support • Environmental: external pressure, external support, government promotion.	223 respondents SMEs education online courses in Pakistan
E-business	(Putra & Santoso, 2020).	• Technology • Organization • Environmental	325 SMEs Indonesian
Smart factory adoption	(Giotopoulos et al., 2017)	• Technological competencies: organizational innovation, R&D activities, Research collaboration	3500 Greek SMEs

		• Human capital: personnel with scientific background, perceived with ICT skills. • Internal organization: decentralized decision - making visionary leadership.	
Electronic data interchange (EDI)	(Kuan & Chau, 2001)	• Technology: perceived benefit • Organization: financial cost, technical competence • Environment: industry pressure, government pressure	575 small firms, Hong Kong
Internet Web site E-commerce	(Martins & Ovivera, 2009)	• Technological context: technology readiness; technology integration; security applications. • Organizational context: perceived benefits of electronic correspondence; IT training programs; access to the IT system of the firm; internet and e-mail norms. • Environmental context: internet competitive pressure; web site competitive pressure; e-commerce competitive pressure.	3155 small Portuguese firms
Smart manufacturing related and digital technologies	(Ghobakhoo & Ching, 2019)	• Technological context: perceived value of SMIDT, perceived cost of SMIDT, perceived compatibility of SMIDT • Organizational context: Information processing requirements, IDT knowledge competency, Strategic Road mapping digitalization. • Environmental context: Imposition by environment, Competitive pressure.	177 Malaysian SMEs 183 Iranian SMEs
Information Technologies	(Chege et al., 2020)	• Technological context: Product innovation Process innovation; Market innovation. • Organizational context Organizational Culture, Innovation parties, Planning & facilitating SD.	242 SMEs Kenya

		• Environmental context: Regulation setting, Economic and Social values, Stakeholder's collaboration.	
Mobile - commerce	(Chau et al., 2018)	• Technological context: Perceived Benefits, Perceived Compatibility Perceived Complexity, Perceived Benefits. Perceived security, Perceived Costs. • Organizational context: Organizational readiness, Top management supports, Strategic orientation, Employee IT knowledge. • Environmental context: competitive pressure, Customer pressure, Government support	SMEs Vietnamese
Cloud computer adoption	(Dincă et al., 2019)	• Technology context: Availability, Characteristics. • Organizational context: Formal and Informal, Linking structure, Communication process size. • Environmental: Industrial, characteristics, Market structure, Technology support Infrastructure, Government regulations	400 SMEs Romanian
Big data Analytics	(Maroufkhani et al., 2020)	• Technology: relative advantage, complexity, compatibility, uncertainty, and Insecurity, Trialability, observability • •Organization, Top management support, Organizational Readiness • Environmental: Competitive pressure, external support from vendors, high degree of regulatory.	171 Iranian SMEs
Social Media	(Sharif et al., 2017)	• Technological: Perceived benefits, Compatibility, Perceived security • Organizational: Formalization	Malaysian SMEs

		• Environmental: Community demand Bandwagon pressure	
Cloud computer adoption	(Khayer et al., 2020)	• Technological context: Relative advantage Service Quality Perceived Complexity, Perceived risk. • Organizational context: Top management supports, Facilitating conditions. • Environmental context: Cloud provider, Server location	450 SMEs Bangladesh
Social commerce	(Abed, 2020)	• Technological context: Perceived usefulness. Security concern. • Organizational context: Top management supports, Organizational readiness. • Environmental context: Customer pressure, Trading partner pressure	181 SMEs Saudi Arabia
e-commerce	(Ghobakhloo et al., 2011)	• Technological context- Perceived relative advantage - Perceived compatibility - Cost • Organizational context: - Information intensity - CEO s' is knowledge - CEO's innovativeness - Business size. Environmental context: - Competition - Buyer/supplier pressure - Support from technology vendors	1, 237 Iranian SMEs
Enterprise systems (ERP) (CRM), (SCM) and e-procurement	(Ramdani et al., 2009)	• Technology: Relative advantage; compatibility; complexity; trialability; observability. • Organization: Top management support; organizational readiness; size. • Environment: Industry; market scope; competitive pressure; external IS support.	SMEs in England

E-commerce	(Rawash, 2021)	• Technology: Relative advantage; Technology readiness; compatibility • Organization: Top management • Environment: competitive pressure; Government support.	Jordanian SMEs

3.19 Conclusion

This chapter discussed the theoretical foundations of technology adoption to understand better how the model established in this study drew on existing models and theories while remaining mindful of their weaknesses and advantages. The chapter reviewed various technology adoption models, highlighting those that have made significant contributions to our understanding of how people, organizations, and society embrace technology. TRA, TAM, and UTAUT were referred to in order to describe how academics interpret the technology adoption process. Each theory and model has its limitations when it comes to explaining the acceptance and deployment of technology. The devised model provides a more holistic view of the factors that lead to positive attitudes toward technology and its adoption in the workplace. The shortcomings of various models related to technology adoption as explained in this chapter show that a new and comprehensive technology acceptance model is needed. A new comprehensive model can fill in the gaps in current knowledge about this topic and provide a high degree of generalizability. This study proposes an advanced digital technologies adoption model based on the TOE, DOI, TRA, TAM, SCT and UTAUT models. The next chapter will discuss the devised and advanced research model of digital technology adoption, and the hypotheses. It will discuss the determinants affecting the adoption of digital technologies in Jordanian SMEs.

CHAPTER FOUR: ADVANCED RESEARCH MODEL AND HYPOTHESES DEVELOPMENT

4.1 Introduction

This chapter discusses the advanced research model, starting with developing the conceptual model and development of the hypotheses. This chapter will explain the variables used in the conceptual model. The eight categories are technological context, organizational context, political-environmental context, socio-cultural context, perception, usage, outcome variables and demographic characteristics. Hypotheses are created based on the literature review for each determinant. Finally, the chapter's conclusion sums up the main points explained in this chapter.

4.2 Development of the Conceptual Research Model

The theoretical foundations mentioned in Chapter 3 serve as the framework for the advanced research model built for this study. This chapter defines the enhanced model in more detail and debates the development of the novel theoretical framework as discussed previously. This study will integrate expected outcome variables as perceived by SMEs in Jordan, to investigate the acceptance and use of digital technologies and their impact on how well they perform. The research model maintains the basic structure of the TAM framework and incorporates some aspects of TRA, TOE, DOI, UTAUT and other relevant theories and models. Several modifications, which were not in these models, are discussed based on an analysis of the relevant literature. The outlined model (Figure 4.1) extends TRA, TOE, DOI and TAM by including the socio-cultural context such as normative beliefs. It appears that socio-cultural context will make a difference (Baker, 2012; Warren, Burton, Buchanan & Birnie, 2016; Clohessy, Acton & Rogers, 2018; Cialdini & Jacobson, 2021). Ajzen and Fishbein (1980) have recommended that external variables can lead to a better understanding of behavioral phenomena. However, these external determinants did not include TRA, TPB, TAM, DOI, or UTAUT. On the other hand, the founders of the TOE model, Tornatzky and Fleischer (1990), argued that internal and external determinants, such as had been included in the (TOE) framework, offer a valuable starting point for studying the adoption of digital technologies. So, this study will use organizational context determinants such as managerial support, training and reward systems, which are essentially external aspects, in developing an advanced model of digital technologies adoption.

The TOE model supports many other models such as the technology acceptance model (TAM) and resolves the shortcomings by including both internal and external determinants (Dincă, Dima & Rozsa, 2019). TOE is an integrative framework that offers a comprehensive and guiding theoretical basis as different technologies are typically evaluated by IT and IS adoption studies (Pumplun, Fecho, Wahl-Islam & Buxmann, 2021). The researcher added perception, usage and demographic determinants based on the TAM model to extend the TRA, TOE, DOI and UTAUT. This study will use four categories of determinants that could affect SMEs' adoption of digital technologies in Jordan: technological, organizational, political-environmental, and socio-cultural. An illustration of the advanced research model is offered in Figure 4.1 below.

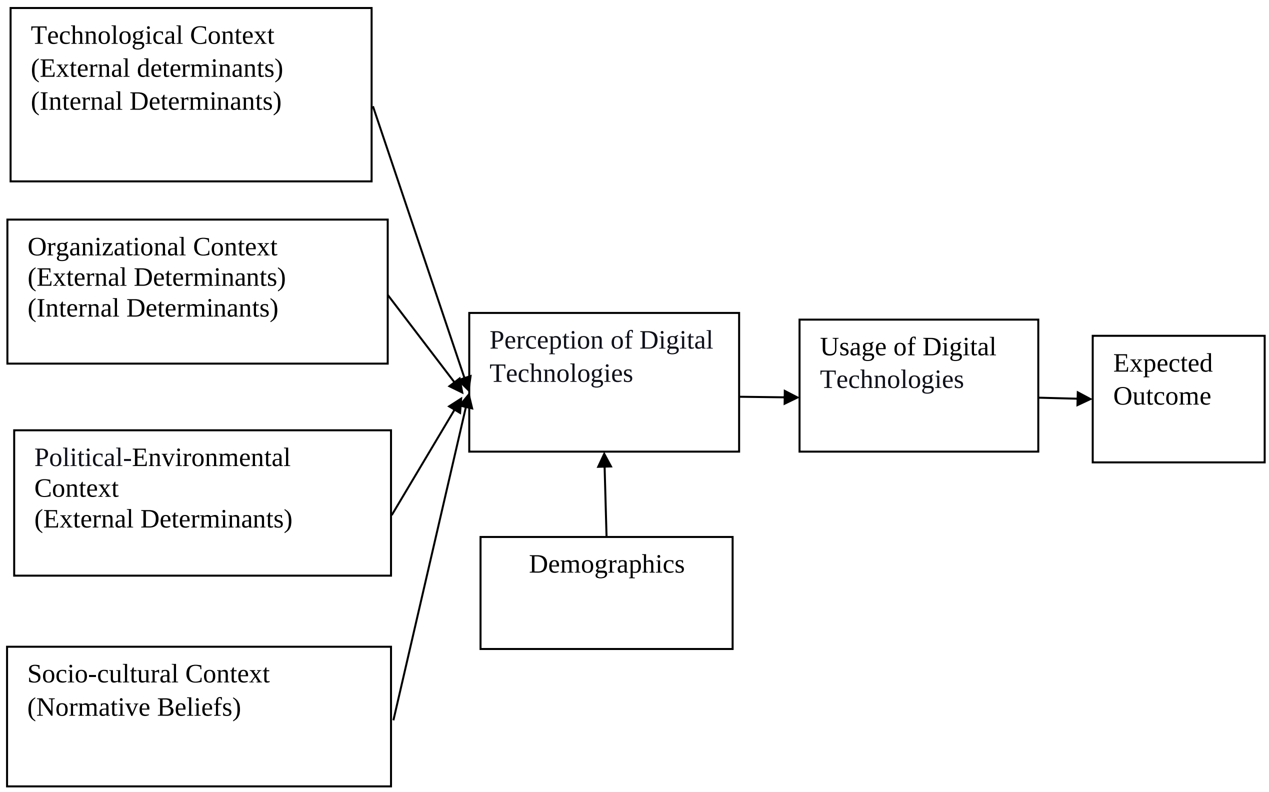


Figure 4.1: Outline of the Research Model

The first category of the conceptual model (Figure 4.1) is called "technological context," and this refers to technology strategy, employees' IT knowledge and technology infrastructure. Khayer, Talukder, Bao and Hossain (2020) state that the technology context defines internal and external (determinants) technologies as being specific to companies (Ghobakhloo & Ching, 2019). The conceptual model matches the technology context of the original TOE model. The theory of DOI is a question-based theory on tools: how, when, and at what rate innovativeness are produced and how ideas and technologies are disseminated across cultures (Arkorful, Barfi & Aboagye, 2021). Thus, the conceptual model adopted DOI theory through technological variables, i.e., Technological infrastructure, and technology strategy.

The second category is known as "organizational context" and this incorporates managerial support, training and reward system. The external determinants were not included in TRA by Ajzen and Fishbein (1980, p. 8), although they mentioned that investigating external factors can help better understand a behavioral phenomenon. Thus, external determinants were included because they emphasize the importance of managerial support, training and reward system determinants. These are very critical to SMEs' perceptions of digital technologies and their usage. Most previous theories and models focused on one aspect. As a result, the conceptual model in this research adopted both external and internal variables. Again, it is emphasized that the TOE model is consistent with DOI theory, in which Rogers (1995) highlighted individual characteristics as drivers of innovation and both internal and external determinants.

The third category of the conceptual model is "political-environmental" and it includes government support/regulations and competitive pressure. It appears that the need for regulations is emphasized because it will shape how things are done legally in the long-term. More stringent regulations or laws can reduce manufacturing costs, boost competitiveness, and spur innovation to offset compliance costs (Ai, Peng & Xiong, 2021). Thus, modifications of environmental context in the TOE model applicable to the political-environmental context in this study's model have been included and combined with external determinants that influence the usage decision. Technology-related problems are not the only variables that assess the acceptance of technologies but other influencers, especially those related to environmental concerns, are also crucial to the preference for a particular innovation (Dincă, VDima & Rozsa, 2019). Gangwar and Date (2016) focus on the technological determinants and the organizational and environmental contexts. Their conceptual research model expanded TOE by adding new determinants: government support and competitive pressures determinants in the environmental context (see Figure 4.2).

A fifth category is also included; it concerns SMEs' perceptions of technological innovation as a dependent variable in relation to drivers. The adopters' attitudes are critical to the innovation-decision process (Rogers, 1995). The sixth category is a dependent variable relative to the fifth category, and it is in fact an independent variable that impacts perceptions of technology usage. Studies have shown that attitude and attention strongly shape usage behavior (Chawla & Joshi, 2021). Likewise, attitudes impact the intentions to do the behavior (Abbasi, Kumaravelu, & Singh, 2021). For the seventh category this refers to outcomes, which comprise a dependent variable to the expected outcomes of adopting digital technologies as perceived by Jordanian SMEs. The outcomes are SMEs': performance (Trinugroho, Pamungkas, Wiwoho, Damayanti & Pramono, 2021), productivity (Lacka, Wong & Haddoud, 2021), profitability (Kumar & Ayedee, 2021), market share (Roseline, Valerie & Abel, 2020), customer satisfaction (Zouari & Abdelhedi, 2021), and sales improvement (Belitski & Liversage, 2019). Lastly, the eighth category is demographics, and it covers: gender, age, education, experience, industry, employees, and role variables. Figure 4.2 depicts the proposed relationships of all independent and dependent variables in the theoretical model.

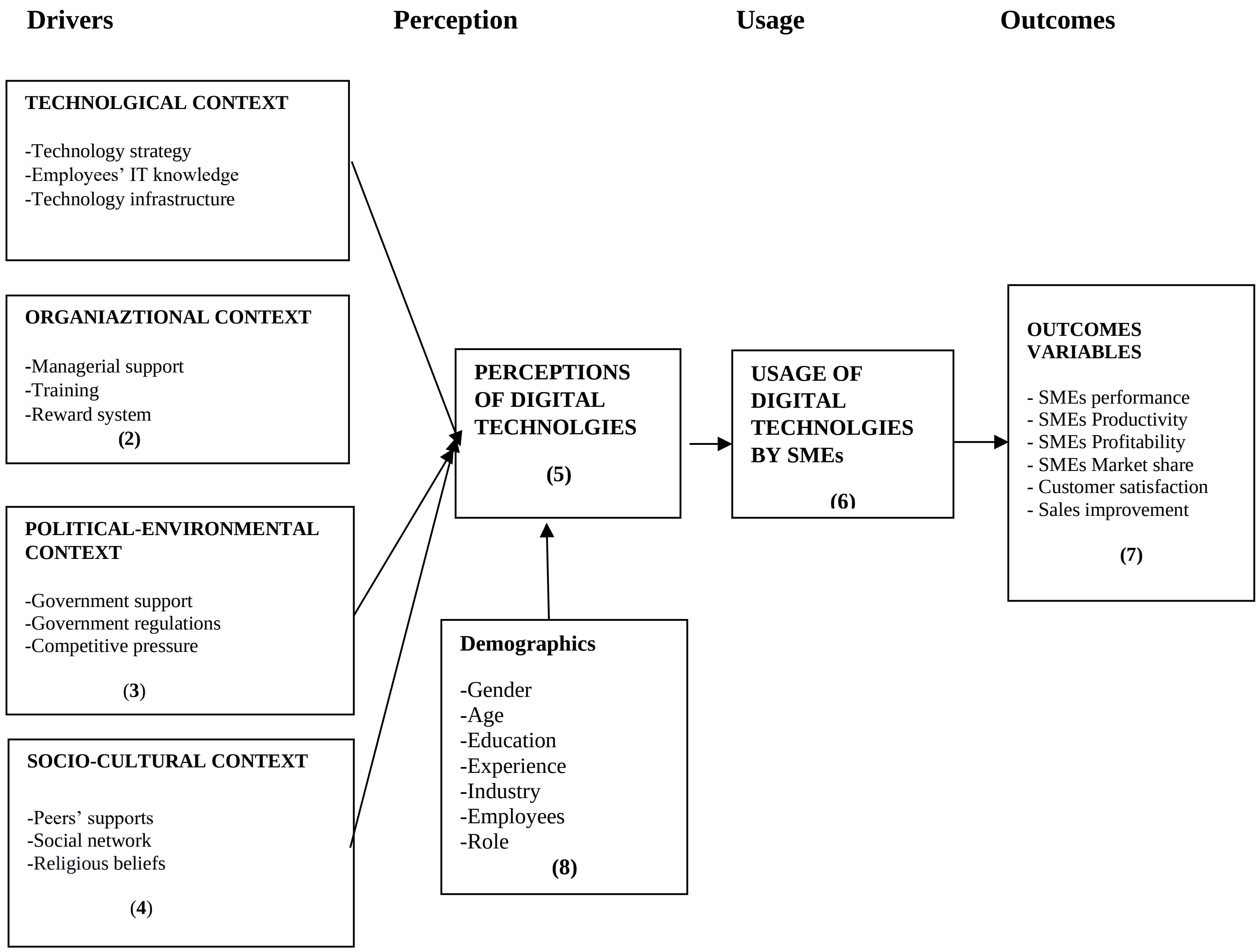


Figure 4.2: Conceptual Research Framework

4.3 Hypothesis Development

This study develops a conceptually advanced model by considering the influence of sociocultural determinant factors, including peer support, social nest work and religious values, and the role they play when people adopt a new technology. The model for this study depends mainly on social cognitive theory (SCT) and the Unified Theory of Acceptance and Use of Technology (UTAUT), with input from the TAM, TRA DOI and TOE models with some modifications. The model contains five categories assumed to significantly influence the adoption of digital technologies in Jordan: technological, organizational, political-environmental, socio-cultural aspects and demographic characteristics. The hypotheses for the study have been derived from this developed model.

4.4 Technological context

The role of technology is a crucial determinant driving innovation in SMEs, and it supports how decisions are made to adopt new technologies (Alrawadieh, Alrawadieh, & Cetin, 2021). The technological context refers to the features of technologies relevant to the firm within the business itself and the overall industry or marketplace (Chau & Deng, 2018). An assessment was made on the adoption technology in SMEs by the OECD (2017, p. 115). It referred to the capacity of SMEs to rapidly adopt new technologies, to get the most out of their production or manufacturing methods despite the constraints of small-scale operations, although there were limits in their ability to benefit from the digital economy. Despite these obstacles, software-as-a-service affords SMEs cost-effective access to technology (Assante, Castro, Hamburg & Martin, 2016). Furthermore, they can switch between technologies if and as required, avoiding costs and lock-in to one IT provider (OECD, 2017). This scenario is now an unparalleled opportunity for SMEs to build a high-quality, flexible, and adaptable IT infrastructure to make digitalization possible. Technological readiness is another determinant that shapes the decision to adopt digital technology in SMEs. In this study's research model the technological context has four variables: technological capabilities, technology strategy, employees' IT knowledge and technology infrastructure. These are explained in more detail below.

Technology strategy

Managerial insights suggest that articulating a digital strategy is the first step in developing a superior digital technology-using firm (Wielgos, Homburg & Kuehnl, 2021). Technology strategies are the primary priority of businesses as they face obstacles and opportunities in terms of emerging economies and innovations (Panda & Sharma, 2021). Companies whose strategic focus is on differentiating their offers are interested in allocating part of their resources to innovation (Chege, Wang & Suntu, 2020). The digital strategy goes beyond understanding that digital resources are ubiquitous in functional areas such as operations, procurement, and marketing (Bharadwaj, El Sawy, Pavlou & Venkatraman, 2013) but pose concerns about: firstly, the reconfiguration of the business model (Clauss, Bouncken, Laudien & Kraus, 2020); and secondly, stages of innovation (Beliaeva, Ferasso, Kraus & Damke, 2019). The digital strategy considers the right resources that meet organizational requirements such as transforming goods and services from a business-centred perspective, and being competitive (Fisher, Kotha & Lahiri, 2016; Grover & Kohli, 2013; Yeow, Soh & Hansen, 2018; Teubner, 2013; Matt, Hess & Benlian, 2015). Dressler and Paunovic (2021) write that for SMEs, digital transformation should be a strategic process that follows one of three paths: (1) customer value proposition, (2) operational model, or (3) simultaneous customer value proposition and operating model change. The lack of a digital strategy leads to bad choices and wasted time and money (Hess, Matt, Benlian & Wiesböck, 2016). Technology strategy is the foundation of an overall business plan which consists of principles, goals, and tactics for using technology to achieve organizational aims. It can, as a result, be hypothesized as follows:

H1. *Digital strategy has an impact on the perceptions of digital technologies in Jordanian SMEs.*

Employees' IT knowledge

Personnel's IT knowledgeability to use various applications are now of great importance to organizations (Verhoef, Broekhuizen, Bart, Bhattacharya, Qi Dong, Fabian & Haenlein, 2019). Continuous learning, training and team development is needed by various digital initiatives with the right blend of skills. The smallness and flexibility of small and medium-sized enterprises (SMEs) present several strengths in this regard, including the ability of the owner and senior management to instil a shared identity that is more likely to promote the exchange of knowledge among employees, particularly during the growth phases (Bouncken & Barwinski, 2020). Beliaeva, Ferasso and Damke (2019) state the challenge facing SMEs will begin to be understood because the opportunities posed by unprecedented technology growth can only be fully realized through the evolution of necessary skills, increased creativity and how the organizational culture develops. SMEs need a mixture of hard skills, such as the ability to use technology and evaluate higher data volumes and soft skills, like solving difficult problems, accepting change, and finding opportunities (Sousa & Rocha, 2019). Extensive research indicates that workers' knowledge and abilities, including strategic thinking, problem-solving skills, and the ability to communicate on networks, are all essential to digitalization (Kiron, Kane, Palmer, Phillips & Buckley, 2016; Sousa & Rocha, 2019). Based on this argument it is hypothesized that:

H2: *Employees' IT knowledge has an impact on perceptions of digital technologies in Jordanian SMEs.*

Technology infrastructure

Digital infrastructure is characterized by Melville and Kohli (2021) as shared heterogeneous, unbounded open, socio-technical systems involving information technologies and processes, communities, and associated capabilities. Moore and Fodrey (2018) argued that a well-designed technology infrastructure has four critical components – systems, objectives, evaluation, and personnel – and that the lack of any of these will likely output unsuccessful technology integration. A robust and scalable IT infrastructure helps businesses innovate and continuously develop products/services to achieve a commercial advantage. IT infrastructure generates company value (Fink & Neumann, 2009). Kashada, Li and Koshadah (2018) stressed that IT infrastructure leads to the successful adoption of digital learning technologies. Lyver and Lu (2018) note that the flexibility of IT infrastructure refers to how an organization's IT infrastructure is flexible, modular, legacy-system compliant, and capable of addressing multiple business applications. Bhatt, Emdad, Roberts and Grover (2010) discovered that IT infrastructures' versatility was positively linked to generating and disseminating information. IT infrastructure's versatility depends on the degree to which it is flexible, compatible, versatile, and able to handle many business applications (Byrd & Tuner, 2001).

Flexible IT infrastructure modularization helps businesses incorporate diverse and geographically dispersed structures. It requires managers to follow and enforce a standard set of IT principles and policies to build and sustain this. Firms can exchange knowledge through internal business units and external stakeholders when standards and policies are in place, and a versatile IT infrastructure enables adapting to changes in the environment (Bhatt, Emdad, Roberts & Grover, 2010; Duncan, 1995; Fink & Neumann, 2007). Similarly, when businesses' IT components are appropriately integrated, they can exchange knowledge and data between different stakeholders. In essence, this integration allows companies to identify fresh ideas quickly, turn these ideas into possibilities for the business, and continuously repeat the process (Lyver & Lu, 2018; Sambamurthy, Bharadwaj & Grover, 2003). Finally, a flexible IT infrastructure enables businesses to progress rapidly and reconfigure existing IT components in response to evolving market needs. On this basis we posit the following hypothesis:

H3: *Technology infrastructure has an impact on perceptions of digital technologies in Jordanian SMEs.*

4.5 Organizational context

The organizational context is the second category of the TOE model that many studies embraced (e.g., Chau & Deng, 2018; Ghobakhloo & Ching, 2019; Abed, 2020; Putra & Santoso, 2020; Park & Kim, 2021; Pumplun, Fecho, Wahl-Islam & Buxmann, 2021). It relates to the attributes and resources for an organization's technology adoption (Chau & Deng, 2018). Management support and financial costs are significant considerations (Park & Kim, 2021). Arnold, Kilian, Thillosen and Zimmer (2018) reported that the determinants of the TOE model are driving the fourth industrial revolution (Industry 4.0), such as management support as an external factor by looking at the specifics of the current information technology revolution from an organizational context (Abed, 2020; Wong, Leong, Hew, Tan & Ooi, 2020), especially in terms of the characteristics influencing what the new technology is expected to do. This study uses the term "organizational context", and it comprises four variables: managerial support, training, and reward system.

Managerial support

Managerial support is anticipated to stimulate digital technology such as big data, like other information systems (Park & Kim, 2021). Ooi, Lee, Tan, Hew and Hew (2018) suggested that managerial support refers to how managers/executives understand the significance of new technologies. Talukder (2014) stated that managerial support refers to the degree to which managerial support helps and motivates employees take up digital technologies (see also Dubey, Gunasekaran, Childe, Papadopoulos, Hazen & Roubaud, 2018). SMEs encounter several difficulties in developing countries when it comes to managerial input, and this concerns the lack of skills (Engwa, Yakum & Mukah, 2021). Managers should understand the effects of external factors and protect the business from extorting and measure external and internal factors such as customers, rivals, vendors, and government regulations that affect ICT innovation trends in companies (Chege & Wang, 2020). Masudin, Aprilia, Nugraha and Restuputri (2021) assert that managers should support technological innovation with creative approaches to manage business activities. Based on these insights, managerial support variables will be used because they are descriptive. This kind of support offers employees assistance in adopting technologies in SMEs, and the following hypothesis is stated here:

H4: *Managerial support has an impact on perceptions of digital technologies in Jordanian SMEs.*

Training

Training is a critical aspect of technology acceptance because theory and research suggest that with adequate technical support and training, staff members' acceptance can greatly improve over time (Zaman, Goldberg, Kelly, Russell & Drye, 2021). Training refers to the scope of training provided to individual workers or teams of workers (Talukder, 2014). It indicates the extent to which training helps increase their knowledge and expertise in using digital technologies. Musteen, Ahsan and Park (2017) reported that, generally, SMEs provide little funding for individual training and development programs for their personnel. Selvarajah, Le and Sukunesan (2019) identified the importance of training as a contributing factor to capacity building to improve SMEs' performance, based on their empirical research conducted in Vietnam. They suggested effective training programs to help them in matters concerning internationalization, such as understanding the cultural nuances of foreign clients and foreign partners, and training programs for networking skills is crucial for building partnerships in international contexts. Thus, training for employees helps SMEs to survive and compete in the digital era (Zaman, Goldberg, Kelly, Russell & Drye, 2021; Chatterjee, Chaudhuri, Vrontis & Basile, 2021). The main objective of the chosen training variable is to develop SMEs' human resources capabilities and how training guides SMEs' perceptions of digital technologies. This study will be using the training variable and the hypothesis for it is stated below:

H5: *Training has an impact on perceptions of digital technologies in Jordanian SMEs.*

Reward system

According to Kim, Wang, and Boon (2021), when businesses implement a new technology, they must hire people who have the necessary skills and knowledge. An incentive or reward system refers to material or other advantages that an organization may provide to employees who use digital technologies (Talukder, 2014). SMEs can devise various rewards or 'carrots' such as wage incentives, job security, bonuses, or promotion (Al-Alawi, Al-Marzooqi & Mohammed, 2007; Hariharan & Cellular, 2005; Lin, 2014). Individuals are more likely to be inspired to complete tasks not because they enjoy doing so but because of the incentive(s) attached (Adler 2013; Roland & Jean, 2003; Seun, Kalsom, Bilkis & Raheem, 2017). Dwivedi, Shareef, Simantiras, Lal and Weerakkody (2016) write that the perception of value for money paid is essential in deciding the intention to adopt technologies. Adler (2013) indicates there is a fairly convincing link between efficiently incorporating the technology into employees' daily workflows and good corporate performance (for example, better sales, better customer service). The concept of social persuasion in a study by Frambach and Schillewaert (2000) terms "incentives" as a reward system and payment for making possible a groundbreaking strategy for organizational change. However, a corporate reward system (or incentive system) may not include financial incentives (Adler, 2013). Accordingly, this study expects a positive relationship between organizational reward systems and digital technologies adoption in SMEs. Here the following hypothesis is suggested:

H6: *Reward system has an impact on perceptions of digital technologies in Jordanian SMEs.*

4.6 Political-Environmental context

Environmental context refers to an external influence such as customers' pressures, suppliers' pressures, and external supports that guide the adoption of technologies, for instance competitive pressure, government policy, and regulations (Chau & Deng, 2018; Park & Kim, 2021). The environmental context was described by Zhu, Kraemer, Xu and Dedrick (2004) as the arena in which a company conducts its business, its industry, rivals, access to resources provided by others, and government relationships. Competitive pressure is a critical environmental factor (Badi, Ochieng, Nasaj & Papadaki, 2021). The TOE model's environmental context helps provide a clearer understanding of the effect on organizations' reaction to external environmental pressures (Gutierrez, Boukrami & Lumsden, 2015; Taylor, 2019). This research examines four variables within the political-environmental context to explain how it guides the implementation of digital technologies by SMEs: government support, government regulations, competitive pressure, and customer pressure.

Government support

The degree to which government activities influence enterprises to promote a given industry or its products and goods/services is called government support (Park & Kim, 2021). Government has an essential role in encouraging innovation uptake or otherwise (Ediriweera & Wiewiora, 2021), and SMEs are not exempt from this. Due to SMEs' role in job creation, social cohesion, poverty alleviation, economic growth, and innovation, governments have increasingly viewed them as important (Ali Qalati, Li, Ahmed, Mirani & Khan, 2021). SME owners, managers, and employees can benefit from government-funded technology training programs and the necessary technological infrastructure (Shaikh, Kumar, Syed, Ali & Shaikh, 2021). In research on SME performance in developing economies, the role of government support and inter-company relationships among SMEs has come to the fore (Manolova, Manev & Gyoshev, 2010). Chisanga, Liao and Shi (2021) note there is a debate on how government funding and inter-company partnerships between small and medium-sized enterprises in developed economies contributes to success, but it is inconclusive. In line with extant small business strategy literature, the conceptual model proposes that government support will affect SMEs' perceptions of digital technologies. Government incentive policies are divided into fiscal, financial, and others (de Jong, Phan & van Ees, 2011). Various forms of direct and indirect subsidies or tax relief provide fiscal incentives, and public subsidies reduce firms' capital, output or credit costs are common financial incentives. Such incentives are advantageous for firms, and it is argued that investment promotion strategies would positively affect their earnings (de Jong, Phan & van Ees, 2011). Thus, the following hypothesis is documented:

***H7**: Government support has an impact on perceptions of digital technologies in Jordanian SMEs.*

Government regulations

Government regulations are closely linked to official legislation (Park & Kim, 2021). Since, for example, the taxation status and trading rules of Bitcoin could change at any time, some risks exist. The theme of how governments deal with data privacy and protection has been given the most significant attention in research related to Big Data. The theme of data privacy and protection focuses on approaches to the challenge of safely distributed data management and data sharing, including what may contain personally identifiable information (Dorr, Greenberg, Fontana, Przybocki, Le Bras, Ploehn, & Chang, 2015). In different ways, many studies have found that legislated data privacy and protection rules are very significant factors that can affect the performance of digital technologies, such as cloud computing in healthcare (Kim & Park, 2017). Surbakti, Wang, Indulska and Sadiq (2020) declared that some security issues have also been recognized regarding data platform use. The usage of third-party providers and (cloud-based) infrastructure to host or perform essential data is substantial and requires government regulation. Hence, the following hypothesis is put forward:

H8: *Government regulations have an impact on perceptions of digital technologies in Jordanian SMEs.*

Competitive pressure

The pressure to take up digitalization from trading partners and customers, and especially in SMEs can be attributed to their need to compete and survive (Ali Qalati, Li, Ahmed, Mirani & Khan, 2021). Competitor and partner pressure effects have been investigated as elements that facilitate the adoption of new IT devices (Park & Kim, 2021). Digital technologies play an essential role in navigating the unpredictable and competitive market/industry environment (Barrales-Molina, Benitez-Amado & Perez-Arostegui, 2010; Müller, Buliga & Voigt, 2018). Digital technologies enable dynamic organizational capabilities (Benitez, Castillo, Llorens & Braojos, 2018). Indeed, digital technologies can allow small and medium-sized enterprises to modify competition rules, alter the business or industry structure, and exploit new strategies to stay ahead of their rivals (Elaine & Patrick 2005; Müller, Buliga & Voigt, 2018). This postulation aligns with other literature (Ghobakhloo & Hong, 2014) and work done on SMEs (Hong & Ghobakhloo, 2013). Generic digital technologies alone cannot be a source of competitive advantage. Compared to late adopters, SMEs who introduce digital technologies ahead of their competitors can make their digital technology resources firm-specific and so are more likely to attain sustained competitiveness. Thus, the following hypothesis is proposed for analysis:

H9: *Competitive pressure has an impact on perceptions of digital technologies in Jordanian SMEs.*

4.7 Socio-cultural context

Different factors play a role in adopting digital technologies but combining the socio-cultural dimensions would provide a rich and detailed contribution to understanding how SMEs do this, to a greater degree (Clohessy, Acton & Rogers, 2018). The impact of socio-cultural attitudes on specific technology domestic diffusion is frequently overlooked in the literature in developing countries (Haque, Lemanski & De Groot, 2021). Shortall and Kharrazi (2017) write that policymakers would better address the threats and challenges of ongoing stakeholder participation when making decisions by recognizing cultural aspects. Although seen as an essential perspective, the socio-cultural dimension needs to be explored in unison with other dimensions to address digital technologies in SMEs. According to DeCanio (1998), failure frequently occurs because decisions are often socially embedded and positively affected by cultural, personal, and institutional constraints (Elmustapha, Hoppe & Bressers, 2018). In their empirical analysis, Auyeung and Sands (1996) showed that in individualistic cultures, the standard is to cope with new and unpredictable circumstances and be creative and adaptive, whereas adaptation and creativity are regarded as problematic in collectivist cultures. The socio-cultural context comprises four variables: social values, peer support, social network, and religious beliefs.

Peer support

The impact of peers refers to the inspiration, motivation and persuasion provided to a person by their peers and friends to adopt a technology (Baudier, Ammi & Deboeuf-Rouchon, 2020). Meanwhile Zorn, Flanagin and Shoham (2011) say it refers to a form of peer impact. Nuryyev, Wang, Achyldurdyyeva, Jaw, Yeh, Lin and Wu (2020) contend that IT adoption is based on peer-to-peer contact and social norms. Direct influence occurs when a peer suggests that a particular technology should be used, and the person may choose to follow this course of action (Talukder, Alyammahi, Quazi, Abdullah & Johns, 2019). The conceptual model uses the "peer support" variable, which is straightforward to understand. Unlike family relationships, friendships are usually a preference relationship, and surveys show that most respondents appear to report positive attitudes towards their peers (Copp, Giordano, Longmore & Manning, 2019). According to Copeland and Zhao (2020), social networks lead the revolution to relationship-building between users of social networking sites and their peers. Furthermore, new generations are increasingly advocating using such channels for everyday use; knowing how they use the web and view the service will affect social networking sites' frameworks and peer relationships (Copeland & Zhao, 2020; Venkatesh, Zhang & Sykes, 2011; Yu, 2012; Zhou, Lu & Wang, 2010). Dickinger, Arami and Meyer (2008) observed little attention was paid to defining communication network externalities in adoption models, i.e., peers' use will lead to more excellent utility and perceived pleasure of another user. It appears that peer support factor shapes digital technologies in SMEs, and the following hypothesis is put forward:

H10: *Peer support has an impact on perceptions of digital technologies in Jordanian SMEs.*

Social Network

Social network refers to how members of other organizations or those of social networks are impacted by workers (Baudier, Ammi & Deboeuf-Rouchon, 2020; Gupta, 2021). The higher the informal exchange of information, the more likely a member will be exposed to new ideas and artefacts (Talukder, Alyammahi, Quazi, Abdullah & Johns, 2019). The social networking platform is an information technology application that best serves the interests of market participants (Turaev, & Ganiev, 2021). Social networks will encourage innovation adoption uptake (Talukder, Alyammahi, Quazi, Abdullah & Johns, 2019) such as Facebook which is a form of social networking (Gupta, 2021). Fisher and Reuber (2011) explained that YouTube as video sharing, Pinterest as image sharing, LinkedIn as technical networking, Blogs as weblogs, foursquare as a location-based social networking website, and Twitter as microblogging, are all social network sites. The term "social network" is used by Venkatesh and Brown (2001). A similar definition was used by Lewis, Agarwal and Sambamurthy (2003) as professional peers, while Brown and Venkatesh (2005) used a concept called "friends and family influence". This study will employ the term "social network" as envisaged by Venkatesh and Brown (2001) and Talukder, Alyammahi, Quazi, Abdullah and Johns (2019). Companies have already begun incorporating social network sites into their practices to sell their innovative features and SMEs are now doing this (Berinato, 2010; Scuotto, Del Giudice & Carayannis, 2017; Betz, Carayannis, Jetter, Min, Phillips & Shin, 2016; Kumar & Ayedee, 2021). However, it seems that mixed results are evident in the empirical literature about the effect of social networking on SMEs’ performance. Thrikawala (2011) and Watson (2007) did find that the commitment of an SME to various networks is helpful to its functioning. Based on this, the following hypothesis will be tested:

H11: *Social network has an impact on perceptions of digital technologies in Jordanian SMEs.*

Religious beliefs

Religious beliefs help people overcome problems in their lives, both big and small, in all situations and places. So it makes sense that during the current COVID-19 pandemic, those who use faith and spirituality to cope with crises will turn back to these beliefs (Wiederhold, 2020). In early 2020, according to an analysis of search results from 95 countries, the number of Google prayer searches increased as the COVID-19 disease spread worldwide. In the same period, a Pew Research Center survey found that most Americans had prayed to end the virus's transmission (Bernstein, 2020). Researchers on management issues have begun assessing employees' religious views as a crucial part of workplace practices (Alsheddi, Sharma & Talukder, 2020). Subsequently, the following hypothesis is proposed:

H12: *Religious beliefs have an impact on perceptions of digital technologies in Jordanian SMEs.*

4.8 Demographic Characteristics

Demographic characteristics can serve as moderating or control variables that reveal individuals’ beliefs and perceptions regarding the adoption of technologies (Eoma, Choi & Sung, 2016; Oliveira, Thomas, Baptista & Campos, 2016; Chawla & Joshi, 2021. This section discusses the demographic variables that are part of the research model. Prior studies on the significance of demographics reveal that gender, age, level of education and other factors such as income, marital status, occupation, and household size are critical determinants in predicting user attitude towards adopting digital products or services (Chawla & Joshi, 2021). Szopiski (2016) discovered that age, income, and education level all substantially affect the use of online banking. Income and career play essential roles in internet banking uptake (Chawla & Joshi, 2021). These are stated in more detail below.

Gender

Gender is crucial to defining human behavior and the decision-making processes of SMEs’ executives, and gender influences how small business owners and managers respond to and use technology (Eze, Awa, Chinedu-Eze & Bello, 2021). Gender can explain the extent to which a person supports gender differences. A person who upholds masculine principles prioritises career-related objectives such as compensation, development, competition, effectiveness and assertiveness. Conversely, those who support feminine ideals prioritize their aspirations, such as a welcoming environment, a comfortable workplace, a high standard of living, and warm interpersonal relationships (Lee et al., 2013). When it comes to technological acceptance, women are more risk-averse than males when embracing new technology (Kapser, Abdelrahman, & Bernecker, 2021). Gender has been found in various studies to play a key role in predicting the usage of technology (Venkatesh et al., 2003; Wang et al., 2009; He & Freeman, 2019). However, despite demographic variables' importance in technology acceptance research, several empirical studies did not investigate the effects of gender as a moderator (Kapser, Abdelrahman & Bernecker, 2021). Radović-Marković, Tomaš-Miskin and Marković (2019) noted that digital technology adoption enables women to cope with gender bias as a way for them to expand their horizons. Subsequently, the following hypotheses is set forward for analysis.

H13: *Gender difference has an impact on perceptions of digital technologies in Jordanian SMEs*

Age

Several studies indicated that age is a significant demographic variable that has a direct and moderating impact on adoption of technology (Venkatesh et al., 2003; Wang et al., 2009; Chung et al., 2010). Chawla and Josh (2020) noted that gender and age influence consumer satisfaction and usage rate in digital technologies such as Smart Mobile wallet adoption (Singh, Srivastava & Sinha, 2017). Trinugroho, Pamungkas, Wiwoho, Damayanti and Pramono (2021) suggest there is also a discrepancy in the usage of digital technologies among owners based on their demographic features, with older people being less likely to do so in the workplace. Hubona (2007, p. 369) asserted that gender and age do affect new technology adoption in a developing country and the following hypothesis is stated:

H14: *Age differences have an impact on perceptions of digital technologies in Jordanian SMEs*

Academic Qualifications

Academic qualifications are one of the most critical variables that can affect the adoption of technological innovations. Top management teams' formal education and competencies significantly shape the extent of technological change in their companies (Wang, Zuo, Yang &

Wu, 2019; Eze, Awa, Chinedu-Eze & Bello, 2021). Rogers (1995) emphasized that innovative leaders are more aggressive in developing something new because of their expertise, talents, and knowledge gained over time and how to weather economic downturns. In general, compared to those who are not educated, education allows people to use technology successfully. Managers and employees who are early adopters of innovation have a higher education level and are more knowledgeable about technology (Porter & Donthu, 2006; Ho & Lim, 2018). Therefore, the following hypotheses has been proposed:

H15: *Academic qualifications have an impact on perceptions of digital technologies in Jordanian SMEs.*

Employment experience

Employment experience is one of the most critical variables that can affect the adoption of technological innovations as well. Costings, productivity, and staff members' confidence are all influenced by experience because this is frequently referred to as a corporate asset (Eze, Awa, Chinedu-Eze & Bello, 2021). On the other hand, top management executives' lack of experience and knowledge of IT capabilities deter adoption (Ho & Lim, 2018; Kübler, Pauwels, Yildirim, and Fandrich, 2018; Huang & Rust, 2018). Hashim (2007) examined the link between senior management executive experience and SMEs' technology adoption. He discovered that when SMEs' experience with IT is enhanced, they develop and comprehend the full potential of IT to advance business endeavours. Therefore, the following hypothesis is put forward:

H16: *Employment experience has an impact on perceptions of digital technologies in Jordanian SMEs.*

Type of Industry

The type of industry as a demographic variable addresses performance variance that may arise due to industry-specific conditions (Oliveira, Thomas & Espadanal, 2014). Types of industry have been frequently used in organizational studies (Lew & Sinkovics, 2013; Ngah, Zainuddin & Thurasamy, 2017; Puta and Santoso, 2020). Therefore, the following hypothesis is worth testing:

H17: *Type of industry has an impact on perceptions of digital technologies in Jordanian SMEs.*

Number of Employees

The definition of SMEs tends to rely on the number of employees. Employees' most critical variables can guide the adoption of technological innovations (Eoma, Choi & Sung, 2016). Su, Yuan, Umar, and Lobonţ (2022) argued that even though employees are being forced out of the workforce, technological advances will eventually increase employment in other sectors that require labor, primarily due to capital accumulation and the rise of digital technologies like automation. With this in mind the following hypothesis is worth testing:

H18: *Number of employees has an impact on perceptions of digital technologies in Jordanian SMEs.*

Role or Position in the business

Role or position is one of the most critical variables that can affect the adoption of technological innovations. It was evident that more senior employees have more sophisticated decision-making duties than lower-level staff (Eoma, Choi & Sung, 2016). The latter will generally not play a role in decision-making and have other types of tasks to do. However, employees could be under pressure to use new technology as directed by their managers. Not many studies have been done on whether workplace position affects technological innovation adoption (Taluder, 2014). Therefore, the following hypothesis is tested:

H19: *Role in business or position has impacts on perceptions of digital technologies in Jordanian SMEs.*

4.9 Perceptions of Digital Technologies and Their Usage

Perceptions refer to positive attitudes toward the system and readiness to participate in the implementation and to adopt the change brought about by the system (Mudawi, Beloff, & White, 2022). The acceptance of digital technologies is affected by users' attitudes to them (Chawla & Joshi, 2021). According to the theory of diffusion of innovations (DOI), Rogers (1995) stated that adopters' attitudes are critical to the decisions made here. When a new technology is presented, potential users assess the potential loss vs the potential gain in accepting the new system (Chatterjee, Chaudhuri, Vrontis & Basile, 2021). A positive perception of digital technologies and a recognition of the strategic role of them from perceived usefulness, perceived ease of use is a significant symptom of readiness and a particular indicator of willingness to adopt digital entrepreneurship in SMEs (Chatterjee, Chaudhuri, Vrontis & Basile, 2021). Thus, there are several factors responsible for influencing a person or organization's decision, including the level of knowledge, awareness of the product, social norm and peer norm, pressure, the propensity to embrace innovation, potential benefits, innovation compatibility and difficulty, observability, or observable results from the implementation of an innovation, and testing or opportunity can thoroughly test innovation before actual engagement (Frambach & Schillewaert, 2002).

Koontz and Weihrich (2010) and Alsheddi, Sharma and Talukder (2020) pointed out that the attitude to a technology is a pre-condition for accepting it. The TAM model contended that users are more liable to accept a system if they consider it to be helpful without a steep learning curve (perceived ease of use) to accomplish a task (perceived usability) (Davis, 1993; Davis, Bagozzi & Warshaw, 1989). The rise of digital technologies has provided many opportunities for SMEs to explore and develop new production methods, raise productivity and growth in the local and international markets, and enjoy good profits. Previous research found that these extrinsic motivations can influence a technology's perceived usability by prolonged usage and ease of use (Eoma, Choi & Sung, 2016; Siala, Kutsch & Jagger, 2019). Furthermore, using new technology gains users' trust and enhances perceptions (Singh & Sinha, 2020). Accordingly, this study proposes the following hypothesis:

H20: *Perception of digital technologies impacts the usage of digital technologies in Jordanian SMEs.*

4.10 Outcome Variables

The desired outcomes of digital technology for SMEs are better performance, productivity, and profitability (Alrawadieh, Alrawadieh & Cetin, 2021). It generates more jobs and sales of higher-quality goods and services (Atkinson & McKay, 2007). The enormous possibilities of these technologies suggest that businesses that ignore them will fade away (Ghobakhloo, 2018; Martinez, 2019; Seyitolu & Ivanov, 2020). However, the expenditures associated with the technology and regulations legislated to support it may make it challenging to invest in them (Kiyohide & Saleem, 2014). In the case of Jordanian SMEs, the primary rationale is that managers make the big decisions about adopting digital technology (Schaefer, Lemmer, Samy Kret, Ylinen, Mikalef & Niehaves, 2021).

SMEs' Performance

Digital technologies can help SMEs perform well (Martinez, 2019; Kumar & Ayedee, 2021; Trinugroho, Pamungkas, Wiwoho, Damayanti & Pramono, 2021). The positive impact of using any digital technology (e.g., EDI, IoT, IOS, RFID) is evident. According to Maroufkhani, Tseng, Iranmanesh, Ismail and Khalid (2020), digital technology significantly helps financial performance, which is also commented on by Hofmann (2017). Khayer, Talukder, Bao and Hossain (2020) found that the inter-organizational introduction of systems helps firms improve operational performance by enhancing flexibility, production lead time, forecasting, cost-saving, resource planning, and inventory level (Chan & Chong, 2012). Market performance is the ability of businesses to achieve more market share, create new markets quickly, and do so successfully (Vitari & Raguseo, 2020; Dong & Yang, 2020). Hence this study suggests the hypothesis as follows:

H21*: Usage of digital technologies has an impact on SMEs' performance in Jordan.*

SMEs' Productivity

Every organization's strategic goal is to increase productivity, which is defined as the ratio of inputs (i.e., resources required to produce outputs) to outputs (i.e., product or service) (Lacka, Wong & Haddoud, 2021). Productivity is considered an essential resource of economic effectiveness and growth and, as such, are the necessary statistical information for many international comparisons and country appraisals evaluations (OCDE, 2011). Digital technologies improve productivity and create new options for delivering better products (Kumar & Ayedee, 2021 (Norris, 2020; Martinez-Caro, Cegarra-Navarro & Alfonso-Ruiz, 2020; Tranos, Kitsos & Ortega-Argilés, 2020). Digital disruption creates significant opportunities to improve productivity growth but comes with lags and change costs (Remes, Mischke & Krishnan, 2018). Remese et al. (2018) asserted that productivity advantages for the industry would materialize mainly when firms restructure what they do. The cost of adoption is outweighed by benefits when digitization reaches a large-scale scenario. Positive and essential relationships have been observed and acknowledged recently concerning the effect of IT investments on organizational productivity levels (Medina, Lavín, Mora & de-la-Garza, 2011). Farrell (2003) believes these relationships are framed and justified in highly competitive environments. SMEs accelerate digital adoption by investing in hard and soft digital infrastructure and clusters, doubling the expertise of digital specialists as well as consumers, ensuring global connectivity, and resolving issues of privacy and cybersecurity (Remes, Mischke & Krishnan, 2018). Müller, Buliga and Voigt (2018) argue that while investing in digital technology implementation such as Big Data may be costly, any input to develop Big Data assets and skills will substantially change companies' productivity. The key determinants of digital technologies in SMEs and how they aer perceived in Jordan lead to the following hypothesis for this construct:

H22: *Usage of digital technologies has an impact on productivity in Jordanian SMEs.*

SMEs’ Profitability

Profitability is a ratio that evaluates firms' ability to generate profits (Gunadi, Putra & Yuliastuti, 2020; Som & Goel, 2021). Digital technology can generate enormous profits if better decisions on innovation, investment and marketing strategies are made (Dong & Yang, 2020; Kauffman & Walden, 2001; Kulatilaka & Venkatraman, 2001). Kumar and Ayedee (2021) write that SMEs will move towards automation-based manufacturing, with scenarios and modelling based on technology for their processes and subsequently create economies of scale; profitability can be increased, allowing SMEs to resolve any financial issues. Businesses have learned how to use IT to maximize profitability through the beneficial effects of consumer loyalty, cross-selling, lower marketing and selling costs (Mithas, Tafti, Bardhan & Goh, 2012). IT-enabled revenue growth is a more potent driver of profitability than IT-enabled cost savings (Mithas, Tafti, Bardhan & Goh, 2012). Qureshi, Ahsan, Aziz and Yousaf (2020) noted that the empirical evidence on the relationship between company size and profitability yields mixed results, but company size is a significant factor in profitability and growth productivity. Furthermore, the resource-based view (RBV) describes a firm's performance as successful if it can create a competitive advantage to generate profit (Qureshi, Ahsan, Aziz & Yousaf, 2020). The following hypothesis is devised:

***H23**: Usage of digital technologies has an impact on profitability in Jordanian SMEs*

SMEs' Market Share

Market share is how much of a market a business has cornered, in other words the percentage of sales a firm has for a current period (Roseline, Valerie, Abel, 2020). Digital technology can influence enable new digital-based businesses to scale up very quickly (Muafi, Syafri, Prabowo & Nur, 2021). According to Gupta, Drave, Dwivedi, Baabdullah and Ismagilova (2020) and Vargo and Lusch (2004), managerial and technological skills needed in predictive analytics for digital technologies like Big Data greatly help with marketing results. According to Akintokunbo (2018) greater market share means that an industry leader can broaden its market reach. Roseline, Valerie and Abel (2020) state that; how well a company is doing against its rivals helps executives determine both primary and selective demand in their market. In addition, it helps them determine the industry's overall growth or decline and developments in customers' preferences. Banbury and Mitchell (1995) claimed that entry timing affects market share and survival, but most of this research addresses paradigmatic technological transition, focuses on entry into new markets, or considers new product introductions as isolated events. Technology innovation generates competition for market share, driving larger companies' profitability lead to other types of entrepreneurial projects for smaller companies (Das, Kundu & Bhattacharya, 2020; Fadahunsi, 2012). Studies have highlighted SMEs' low level of improved technology is a critical problem in developing countries and held back their world trade prospects and success (Das, Kundu & Bhattacharya, 2020). Hence, the market share outcomes variable is significant for SMEs and developed here is the following hypothesis:

***H24**: Usage of digital technologies has an impact on market share in Jordanian SMEs.*

SMEs' Customer Satisfaction

Consumer satisfaction is described as a general assessment based on the overall purchasing and consumption experience of the customer with a product or service and capabilities of a business, based on surveys and reviews (Nugroho, Susilo, Fajar & Rahmawati, 2017; García-Madariaga & Rodríguez-Rivera, 2017; Zouari & Abdelhedi, 2021). People's lifestyles and consumption habits are changing due to newly created and deployed technology, which significantly changes the nature of business-customer relationships (Zouari & Abdelhedi, 2021). Customer satisfaction has been identified in the marketing literature as a significant part of corporate strategy (Fornell, Mithas, Morgeson & Krishnan, 2006), a primary indicator of long-term corporate profitability (Gruca & Rego, 2005). Several empirical studies show that firms have learned how to make use of IT to improve customer satisfaction, at the same time boosting profitability through creating customer loyalty, cross-selling, and reduced marketing and selling costs (Fornell, Mithas, Morgeson & Krishnan, 2006; Mithas & Jones, 2007; Zouari & Abdelhedi, 2021; Srinivasan & Moorman, 2005). Raza, Umer, Qureshi and Dahri (2020) document that the technology-based system's progress has created an entirely new approach for companies to communicate with their customers. For example, Internet banking is a platform that enables people to access different services, such as bill payments and investments (Wang & Kim, 2017). Anderson and Srinivasan (2003) claim that e-satisfaction refers to the satisfaction of users about transactions or dealing with online services. Therefore, this study developed the following hypothesis for this construct:

***H25**: Usage of digital technologies has an impact on customer satisfaction in Jordanian SMEs*.

SMEs' improved sales

In the economies of many developing countries, small- and medium-sized enterprises (SMEs) play an essential role. Information and communication technology significantly influences society and businesses (Van Wart, Roman, Wang & Liu, 2017). As a result, SME leaders face a crucial challenge in implementing digital technology to generate value and faster production speeds to improve sales (Belitski & Liversage, 2019). Ghobakhloo and Ching (2019) stated that digital technologies boost performance by contributing to sales improvement, improving customer satisfaction, supplier connections, and promoting the business's capabilities (Çallı & Çallı, 2021). Belitski and Liversage (2019) asserted that the constraints associated with restricted access to capital, low ability levels, ineffective leadership, and sluggish adoption of digital technology are the obstacles facing SMEs in developing countries. There is no efficient coordination between SMEs and ICT operations in these conditions, and the commercialization of new goods could be delayed (Belitski & Liversage, 2019). Therefore, SMEs will seek to increase information technology diffusion in developing economies to promote business and increase sales (Li, Liu, Belitski, Ghobadian & O'Regan, 2016; Ramamurthy & Premkumar, 1995). Whether it is smartphone applications, social networking, the Internet of Things, or any other technologies, companies need to take advantage of new ideas, gather feedback, etc., to sell their goods and services (Belitski & Liversage, 2019). In addition to strategic resource management, knowing the market and being ICT savvy will enable complementarity (Li, Liu, Belitski, Ghobadian & O'Regan, 2016), so that a framework can be devised to understand clients through technology, to achieve greater customer satisfaction through posting and sharing information on Instagram, Facebook, and other digital platforms (Ferneley & Bell, 2006; Belitski & Liversage, 2019). On this basis the following hypothesis was devised for this construct:

H26*: Usage of digital technologies has an impact on improved sales in Jordanian SMEs.*

Table 4.1 below documents the four research questions and their corresponding hypotheses. The first research question of this study examines the impact of four broad context determinants (technological, organizational, political-environmental, and socio-cultural) on the perceptions of digital technologies among SMEs in Jordan. The twelve hypotheses listed are specific statements that aim to test the relationship between different determinants within each of these determinants and SMEs' perceptions of digital technologies. The hypotheses related to technological determinants (H1 to H3) suggest that digital strategy, employees' IT knowledge, and technology infrastructure could influence SMEs' perceptions of digital technologies. The hypotheses related to organizational drivers (H4 to H6) suggest that managerial support, training, and reward systems could impact SMEs' perceptions of digital technologies. Meanwhile, hypotheses related to political-environmental drivers (H7 and H8) suggest that government support and regulations and competitive pressure could influence SMEs' perceptions of digital technologies. Lastly, hypotheses related to socio-cultural drivers (H10 to H12) suggest that factors such as peers' support, social network, and religious beliefs could impact SMEs' perceptions of digital technologies. These hypotheses seek to explore the various determinants that could shape SMEs' perceptions of digital technologies in Jordan, providing insights into how to foster greater adoption and use of such technologies among this group.

The second research question "What is the impact of demographic characteristics on SMEs' perceptions of digital technologies?" examines how the demographic characteristics of individuals within small and medium-sized enterprises (SMEs) in Jordan affect their perceptions of digital technologies. The seven hypotheses listed relate to specific demographic characteristics that the researchers believe may impact SMEs' perceptions of digital technologies. These hypotheses suggest that gender, age, academic qualifications, employment experience, type of industry, number of employees, and role in business or position may all be influential factors. By testing these hypotheses, the study aims to identify which demographic characteristics significantly impact SMEs' perceptions of digital technologies. This information could be helpful for policymakers and businesses looking to improve the adoption and use of digital technologies in Jordanian SMEs.

The third research question "What is the impact of SMEs' perceptions of digital technologies on usage level?" seeks to investigate whether SMEs' perceptions of digital technologies impact their usage. The hypothesis, "A perception of digital technologies impacts the usage of digital technologies in Jordanian SMEs," proposes a tentative relationship between SMEs' perceptions of digital technologies and their usage levels. It suggests that if SMEs have a positive perception of digital technologies, they are likely to use them more frequently than those with a negative perception.

The fourth research question "What are the expected benefits to Jordanian SMEs from usage and adopting digital technologies?" predicts specific benefits that Jordanian SMEs can expect from using and adopting digital technologies. The six hypotheses listed are specific predictions about the benefits that Jordanian SMEs can receive from using and adopting digital technologies. Each hypothesis directly relates to the research question, which seeks to understand the expected benefits SMEs can receive from using and embracing digital technologies. For example, H21 indicates that using digital technologies impacts SMEs' overall performance in Jordan, suggesting that SMEs that use digital technologies will perform better than those that do not.

Table 4.1 Research questions and corresponding hypotheses

Question Number	Research Question	Corresponding Hypotheses

RQ1	What is the impact of technological, organizational, political-environmental, and socio-cultural determinants on SMEs' perceptions of digital technologies?	H1, H2, H3, H4, H5, H6, H7, H8, H9, H10, H11, H12
RQ2	What is the impact of demographic characteristics on SMEs' perceptions of digital technologies?	H13, H14, H15, H16, H17, H18, H19
RQ3	What is the impact of SMEs' perceptions of digital technologies on usage level?	H20
RQ4	What are the expected benefits to Jordanian SMEs from usage and adopting digital technologies?	H21, H22, H23, H24, H25, H26,

4.10 Conclusion

This chapter has discussed the advanced research model for assessing digital technologies adoption in SMEs and the chosen hypotheses. The conceptual model is based on the Technology Acceptance Model (TAM) and incorporates technology adoption models' elements. The chapter pointed out that digital technologies are a critical instrument for boosting the efficiency and performance of any organization, especially SMEs and other aspects of their operations such as productivity and profitability. The conceptual model contains five contextual determinants - technological, organizational, political-environmental, socio-cultural and demographic characteristics. Within the four categories of determinants, there are twelve independent variables (managerial support, training, reward system, technology strategy, employees' IT knowledge, technology infrastructure, peers support, social network, religious beliefs, government support, government regulations and competitive pressure). The fifth category comprises demographic characteristics (gender, age, education, employment experience, industry, employees, and role) variables. Each determinant has been assessed using evidence from the literature, and hypotheses emerged from the evaluation.

The framework demonstrates the relationship between these characteristics and users' attitudes to digital technologies and their adoption behaviors. These variables affect the adoption of digital technologies by characteristics of potential users. The proposed advanced model is easy to recognize, and it is more rigorous than many models such as the TRA, TAM, DOI, TOE, TPB, and UTAUT variants. The original TRA, TAM, DOI, TOE, TPB models have fewer variables and no moderating variables. This research does not include complexities compared to the previous models and theories, which provide greater explanatory power in a practical environment. Institutions pursuing and diffusing digital technologies may find the presented conceptual model helpful. There is a need to manage and apply technologies appropriately, and take into account cultural practices and social situations, and political-environmental considerations. The model will be examined using an empirical study and should yield meaningful results to comprehend what drives the adoption of digital technologies in Jordanian SMEs. The next chapter will discuss the methodology used in this study.

CHAPTER FIVE: RESEARCH METHODOLOGY

5.1 Introduction

This chapter will discuss the research methodology employed in this study. Covered here are the research philosophy, research design, location of the study, reasons for using artificial intelligence, quantitative research method and a discussion of the sample frame, sample population for the study, variables of the study, construct of measurement, reliability and validity issues, pilot study, data collection procedures and analysis techniques. Ethical issues are discussed in the sixth and last section. The decisions made regarding the methodology were determined by the overall research objectives, to investigate the practice of digital technology adoption in Jordanian SMEs using a new conceptual framework.

5.2 Research Philosophy

Research philosophy is a set of beliefs about how evidence on a topic should be gathered, analyzed, and applied (Mbaya, Maina & Namusonge, 2021; Creswell & Poth, 2018; Kumatongo & Muzata, 2021; Saunders, Lewis &Thornhill, 2019). According to Saunders (2011) there are four significant research paradigms: ontology, epistemology, methodology, and methods. The ontology research paradigm refers to theories and assumptions concerning how to identify a topic's social phenomenon or context. Hence, it is required for research to determine whether the paradigm's values, beliefs, assumptions, and norms are appropriate for addressing the question(s) or not (Kivunja & Kuyini, 2017). There are three commonly used research philosophies: realism, positivism and interpretivism: realism depends on independent ideas of the human mind's scientific assumptions, whereas positivism relies on scientific observation and adequate measurement; therefore, it only takes factual data into account (Kivunja & Kuyini, 2017). Interpretivism believes in incorporating human interest into research and deciding what are the key elements to develop assumptions that assess reality (Kivunja & Kuyini, 2017). The positivist paradigm is quantified, in which hypotheses are evaluated and objective measures are taken (Mbaya, Maina & Namusonge, 2021). Also, truth is regarded as distinct from the researcher, and the presumption is that it can be observed directly (Wimmer & Dominick, 2013). The positivist model is thus synonymous, ontologically speaking, with the perception that social truth is objective and external (Foroudi, Palazzo & Stone, 2021). The positivist paradigm's axiological paradigm is value-free and unbiased, and it is assumed that nature is objective, singular and thus separate from the researcher (Introna, Kavanagh, Kelly, Orlikowski & Scott, 2016; Foroudi, Palazzo & Stone, 2021).

The positivist paradigm approach is a deductive process that helps identify the cause and effect. It provides accuracy and reliability, and with the help of generalization, it provides prediction, explanation, and understanding (Mbaya, Maina & Namusonge, 2021). The language of study is quite formal and is based on set definitions using accepted quantitative words. Epistemologically, the quantified data, truths and information constitute adequate knowledge (Wayhuni, 2012). In the current research, the positivist philosophy will be used because this study sets to interpret the adoption of digital technologies by SMEs in Jordan. This strategy to build knowledge aligns with Saunders, Lewis and Thornhill's (2019) ideas, and the philosophical stance (research paradigm) used is post-positivism (Sultan, Zafar & Jatoi, 2021). Epistemology applies to knowledge concepts, proper, correct, and appropriate knowledge, and how we can share knowledge with others (Burrell & Morgan 2017; Mbaya, Maina & Namusonge, 2021).

Four types of experience can determine the research's epistemology: logical knowledge, intuitive knowledge, authoritative knowledge, and empirical knowledge (Kivunja & Kuyini, 2017). For this thesis, logical knowledge will be applied because it helps gain insights into the subject through the inference principle that preserves truth. The questions have been constructed, keeping in mind that the positivist approach has been selected. The research questions will help us to identify the determinants that impact SMEs' perceptions of digital technologies in Jordan and how they will be used. Also, the research questions are designed to lead to persuasive arguments, and the survey conducted will be linked with a high level of validity as the data in these studies must be trustworthy and honest. The positivist approach will aim to provide methods and answers for developing and understanding the primary four contexts focusing on technological, organizational, political-environmental and socio-cultural determinants of adoption of digital technologies in the SMEs sector in Jordan and its impact on their performance and other outcomes variables.

5.3 Research Design

The research design is a framework that encompasses certain components to be considered when addressing a research problem (Alqahtani, 2016). All research approaches have underlying philosophical assumptions (Creswell & Poth, 2018). Three general approaches are generally distinguished from the methodological perspective in business analysis: the quantitative, qualitative and participatory action approaches (Marais, 1988; Gable, 1994). The research design can follow the research objective as explanatory (qualitative) or exploratory (quantitative) (Gravetter & Forzano, 2015; Mbaya, Maina & Namusonge, 2021). Questions based on 'how' and 'why' factors are used in exploratory (quantitative) research (Sekaran & Bougie, 2019). Researchers mostly use one of the three research designs to ensure that the study is conducted ethically. A qualitative (explanatory/ descriptive) research design is used to research problems that have not been investigated earlier, whereas an explanatory (quantitative) research design measures one variable's impact over another variable (Creswell & Poth, 2017). The argument between inductive (qualitative) and deductive (quantitative) is the two approaches researchers have used. When there is a need to find and develop new theories and models, inductive research is employed. For the older available methods, deductive research is used, and this demands a good understanding of the topic and answering the questions (Creswell & Poth, 2017). The deductive (quantitative) research method helps the researcher formulate a hypothesis and gather evidence and data to validate or refute it (Gill & Johnson, 2010; see Chapter 4 of this thesis for more details on this). Furthermore, in this research, the deductive (quantitative) strategy will provide the possibility of explaining relationships between ideas and variables. The primary justification for conducting deductive (quantitative) research is to enhance the robustness of a proposed research design. Data collection and analysis using various instruments is necessary to answer specific questions and satisfy established objectives (Creswell, 2013, 2014). Hence, descriptive methodology emerges as the best option to carry out this study as it helps to gather and analyze relevant data. Data will be collected; the researcher will find some determinants that have led to such changes in the SMEs' perceptions of digital technologies. Finally, the researcher will discuss how technology adoption can help SMEs do well. Although adoption of digital technologies has been extensively studied in advanced nations, there is still very little known about digital technologies in countries like Jordan. The research design is summarized in Table 5.1 below.

Table 5.1 Research design: Exploratory Sequential Design

Research Methods	Quantitative research design
Sample	On a randomized basis, this study targeted to reach (1200 – 1600). This is to achieve a 25%-30% rate for generalizability of the research guideline Hair et al. (1998).
SMEs in different industries	Construction and building material, Automotive-related repair maintenance & traded, Wholesale and retail trade (non-automotive, Finance and insurance, Food & beverage, Agriculture, Information, communication & technology, Tourism, Real estate and other services.
Questionnaires	Online survey Questionnaires - Link by email. Questionnaires was distributed to 1600 SMEs in Jordan.
Length of questionnaires	107 Questionnaires including: measure demographic, usage level of AI, independent and dependent variables.
The contents of the questionnaires	First part: Demographic information of the respondents including seven variables. Second part: usage level. Five indicators will be used to measure usage level of digital technologies (Actual amount of time spent, frequency of use or job-related work? level of usage, number of used different applications and use advanced features of digital technologies. The third part: independent variables including technological, organizational, political- environmental and socio-cultural determinants questionnaires. The fourth part A perception towards digital technologies. The fifth part: Dependent variables including performance, productivity, profitability, market share, customer satisfaction and sale improvement.
Participants	Owners/Managers in SMEs at Amman the capital Jordan. The Justification of selection management only in SMEs. Because adopted the scholar's statement e.g. (Rogers (1995) emphasized that innovative management leaders are more aggressive in developing something new because of their expertise, talents, and knowledge gained over time to resurrect the organization during economic downturns profitably.
Number of Participants Targeted	Achieve the targeted number of respondents of 300 – 400 Participants. This is to achieve a 25%-30% rate for generalizability of the research guideline – Hair et al. (1998). This study reached the rate of 25 %.

5.4 Location of the Study

The study will be conducted on SMEs in Amman, the capital of Jordan. Amman is Jordan's most populous city and the country's economic, political, and cultural centre and technological infrastructure, including active Internet. SMEs have long recognized that technological innovation is a crucial driver for improving their competitive advantage. Jordan's government has recently focused on using digital technologies in a range of sectors to transform the rationale of SMEs through digital services. This policy has helped the country rise in the league tables for digital connectivity and internet readiness, and it has also attracted investment from foreign companies (Budde, 2021). The research questions will be tested in the context of the Artificial intelligence as the primary tool for the digital technologies used by SMEs' managers. The approach of this study is using a quantitative method for collecting the data.

5.5 Reasons for Using Artificial intelligence.

The usage of digital technology is a challenging task to measure comprehensively, as highlighted by various researchers (van Dijk (2012), Ragnedda (2019), Warschauer (2003), Warschauer and Matuchniak (2010), Hargittai (2010), DiMaggio et al. (2004), and Ragnedda (2017). The complexity and multifaceted nature of digital technologies makes it difficult to assess them accurately unless measured by a specific type of measurement tool, such as Artificial Intelligence (AI). Therefore, this study has chosen AI for several reasons to measure the usage of digital technology in Jordanian SMEs. AI refers to software and hardware systems created and designed by humans (Su, Yuan, Umar, & Lobonţ, 2022), which can perceive their surroundings by collecting data, analyzing structured or unstructured data, processing the information derived from these sources, and deciding on the best course of action to achieve a given goal (Von Solms & Langerman, 2022).

The uniqueness of AI technology lies in its ability to analyze vast amounts of data and identify patterns and trends that would be difficult for humans to discern. Therefore, digital technologies require a specialized measurement tool like AI to accurately assess their usage and impact, as emphasized by Lee & Lee (2015) and Kshetri (2018). For instance, the Internet of Things (IoT) has numerous applications and presents significant challenges for enterprises in managing and analyzing data (Lee & Lee, 2015). Similarly, Kshetri (2018) discusses the potential of blockchain technology in supply chain management and the need for specialized tools like AI to collect and analyze the massive amounts of data generated by these systems. Digital technologies require technical measurement and tools such as AI to assess and evaluate accurately.This study examines the use of artificial intelligence in the SMEs in Jordan. Although artificial intelligence is relatively new in businesses, SMEs are keen to use it in the age of technology, business competitiveness and globalization. AI will dictate the future and nature of the economy (Parente, Silva, Junior & Uhlmann, 2022; Ulrich & Frank, 2021).

AI is part of a new wave of technologies to help businesses gain a competitive advantage and reach targeted customers on a global scale. It seems that AI is a broad term that incorporates a variety of methods - machine learning and deep learning will be used as synonyms for AI, which means communicating how a computer can learn patterns based on inputs (Hansen & Bøgh, 2021). AI primarily focused on larger enterprises and especially software giants such as Google and Facebook (Hansen & Bøgh, 2021). However, SMEs are becoming increasingly interested in wanting access to these technologies, given that recently the COVID-19 pandemic made corporations and governments more about how the artificial intelligence can be utilized to preserve social distancing, do business tasks from a safe location, improve customer delivery, and still retain the competitive edge (Kumar & Kalse, 2021).

Natural language processing, robotics, cognitive modelling, machine learning, expert systems, knowledge representation, and heuristic problem-solving are some of the more general fields of AI (Ulrich & Frank, 2021). AI enables SMEs to achieve world-class production standards and marketing operations with minimal human staff, reducing costs and increasing revenues while ensuring humanity's safety (Kumar & Kalse, 2021). For example, QR codes are primarily used for inventory management. Still, when integrated with artificial intelligence, they can be used for various tasks, such as accounting, recognizing client preferences, projecting future demand, and thus enhancing production efficiency (Kumar, 2020). In addition, AI can help SMEs battle tacit knowledge by leveraging technology like decision support systems (Hansen & Bøgh, 2021). Marketing, financial record keeping, accounting information systems, reducing commercial risks, improving overseas market expansion, and improving productivity are all areas where artificial intelligence can help SMEs (Kumar & Kalse, 2021), such as monitoring clients' online behaviors, managing demand-supply, and handle all back-end processes (Kumar & Kalse, 2021). It can examine a consumer's behavior when it comes to purchasing patterns, satisfaction, demands, demography, and preferences (Haenlein & Kaplan, 2019; Kumar & Kalse, 2021; Prentice & Nguyen, 2020).

Artificial intelligence has numerous applications in businesses of all sizes, with chatbots being one of the most popular. They can be implemented quickly and at a lower cost compared to other AI applications, making them a cost-effective option for many businesses. According to Deloitte (2019), ease of implementation and affordability are two reasons why chatbots are an attractive option for businesses of all sizes. The global chatbot market size was valued at USD 2.6 billion in 2019, with a compound annual growth rate (CAGR) of 24.3% expected from 2020 to 2027 (Grand View Research, 2020). Advancements in AI and machine learning technologies have made speech and voice recognition systems more affordable and accessible to businesses of all sizes, according to a report by Markets and Markets (2020). Moreover, chatbots are relatively cheap to implement, which adds to their appeal for businesses looking to leverage AI technologies to improve their operations. However, it is crucial for organizations to weigh the costs and benefits of adopting AI technology before making a decision. This involves considering both the direct costs of implementing and maintaining the technology and the potential benefits in terms of improved efficiency, productivity, and customer satisfaction. Therefore, while chatbots and other AI applications may offer cost-effective solutions, businesses should carefully evaluate their specific needs and goals to ensure that they are making the most informed and strategic decision.

5.6 Quantitative Research Design

The quantitative approach is closely linked to the positivist viewpoint, wherein the emphasis is on measurable facts and testing theory (Foroudi, Palazzo & Stone, 2021). This approach is concerned with queries such as "How much?" and "How often?" (Nau, 1995). Creswell (2013) claims that this approach is best for discovering determinants that influence the results of a social issue. Quantitative research is defined by Creswell (2013) as a method for investigating the relationship between variables in order to test objective theories. These variables can then be monitored using devices, allowing numbered or tabulated data to be analyzed using statistical procedures (Creswell, 2013). It appears that questionnaires, surveys, field and laboratory tests, and statistical data obtained by organizations are all examples of quantitative research methodologies (Cavana, Delahaye & Sekaran, 2001). Quantitative studies evaluate hypotheses deductively, employing prior information to generate and suggest hypothetical relationships and outcomes, all of which can aid in producing scientific findings (Bryman, 2012). Alshirah, Lutfi, Alshirah, Saad, Ibrahim and Mohammed (2021) write that quantitative method tests the relationships between independent and dependent variables. Lovett, Brinckley and Jones (2021) described the quantitative analysis as a mixture of testing objective theories by examining the relationship between variables, which should be measured consistently using accepted methods (Creswell, 2013). Altameem (2007) states that quantitative approaches carefully choose targets that need to be explained. Creswell (2007, 2013) argues that this strategy is most appropriate for defining variables influencing a social problem's outcomes. Table 5.2 lists a few key differences between the quantitative and qualitative methods.

Table 5.2: Quantitative versus Qualitative Research

Highlights	**Quantitative**	**Qualitative**
Epistemological perspective	Positivist	Interpretivist
Research purpose	Deductive, describe, predict build and test theory and hypothesis testing	Inductive and in-depth understanding theory building
Sample design	Probability	Nonprobability- purposive
Sample size	Large size	small Size
Research design	Determined before stating the study, uses method or mixed methods and consistency is critical.	Adjust and may evolve during project.
Participant preparation	No preparation desired to avoid biasing the participant	Pre-tasking is common
Data type	Produce precise, quantitative data that can be converted into numerical codes for electronic processing.	Produce "rich" qualitative data that can be converted to verbal codes (sometimes with computer assistance)
Data analysis	Computerized analysis statistical and mathematical, analysis maybe ongoing during the project and maintains clear distinction between facts and judgement.	Human analysis is performed after computer or human coding and is primarily non-quantitative and continues throughout the project. The researcher is forced to consider the phenomenon's contextual framework. The boundary between facts and judgments is less clear when measured
Findings	Allow outcomes to be generalized from the sample to the population.	Allow outcomes to be generalized from one setting to another similar setting

Sources: Collis and Hussey (2009), Bell and Bryman (2007), Bryman (2012), Creswell (2013), Foroudi, Palazzo, Stone (2021) and Walters (2021).

Quantitative research test variables accurately to quantify data and generalize the findings to a larger population or context. and thus, confirming the validity of a given theory (Talukder, 2014; Foroudi, Palazzo & Stone, 2021). In the quantitative method, the researcher uses a literature review to classify questions and variables linked to a general causal explanation or interrelationship before collecting actual data. When analyzing a situation or a phenomenon, the researcher should remain distant and try to control bias and be "objective." It is defined as traditional, empirical, and experimental (Creswell, 1994). It appears that quantitative data analysis relies very heavily on statistical principles, so for this research, an online survey questionnaire served as the primary quantitative data collection method; statistical analysis is carried out using the SPSS 27 software package.

This study develops an experimental design in which the dependent variable/s are tested for the effects of selected independent variables, so the relationships between them are established. A variety of statistical tests will be carried out to test the model to establish the significance of each model variable. The study will investigate the impact of independent variables (drivers) on dependent variable/s (perception and usage level); therefore, the quantitative approach is deemed appropriate to analyze the data. As shown in Table 5.3, similar studies that employed quantitative methods are stated.

Table 5.3: Studies on digital technologies that have applied quantitative method.

Authors	**Geographical and Organizational Context**
Won and Park (2020)	3700 SMEs in South Korea
Putra and Santoso (2020)	325 SMEs in Indonesia
Giotopoulos et al. (2017)	3500 Greek SMEs
Wong et al. (2020).	194 Malaysian SMEs
Martins and Ovivera (2009)	3155 small Portuguese firms
Ghobakhoo and Ching (2019)	177 Malaysian SMEs and 183 Iranian SMEs
Chau and Deng (2018)	172 SMEs in Vietnam
Dincă et al. (2019)	400 SMEs in Romania

Maroufkhani et al. (2020)	171 Iranian SMEs
AlSharji, et al. (2017)	1,700 UAE SMEs
Khayer et al. (2020)	450 SMEs in Bangladesh
Abed (2020)	181 SMEs in Saudi Arabia
Ghobakhloo et al. (2011)	1, 237 Iranian SMEs

5.7 Sampling Frame for the Study

This study is one of the first on adopting digital technologies by small and medium-sized enterprises (SMEs) in Jordan, where they are the backbone of the economy because they employ most of its people (OECD, 2019). Rather than a multi-country analysis, the reason for choosing a single country was to remove the macro-environmental diversity that would complicate the research. It is anticipated that data collection in a reasonably homogeneous environment would further make it easier to explain what is happening, unlike when uncontrollable external variables are involved (Amine & Cavusgil, 1986). The reason for choosing Jordan is that the researcher is a native of the country and has worked in the private and public sectors. Jordan has only few natural resources and most investment has been in technology and infrastructure for most of its industries (Lukonga & Joshi, 2020).

This study will provide data from Jordan to enhance generalizability of the findings to the broader region in many ways especially after the Digital Cooperation Organization (DCO) was launched in 2020 involving Jordan, Kuwait, Bahrain, Saudi Arabia, and Pakistan (Access Partnership, 2021). One of the most important aspects of any survey is sampling because it forms the basis for the main generalizability argument, which is the primary strength of any study. Biemer and Lyberg (2003) stated that particular interest groups might be over-sampled, or sampling may be based on a salient result. Sampling design selection also balances research objectives and the costs of conducting the survey. Wetcher-Hendricks (2011) clarified that quantitative data also requires random sampling. Saunders, Lewis, Thornhill and Bristow (2019) write that the complete list of all the total population cases from which the sample is taken is the sampling frame (see also Sanders, Clarke, Stewart and Whiteley, 2007). The author of this study obtained the contact details of SMEs in Amman from the official Amman

Chamber of Commerce (2022) website. Questionnaires were sent it to SMEs by email. The sampling frame of this research included several types of SMEs that operate in and around Amman.

The current study's sample size includes 1600 SMEs. Owner and managers of SMEs are the target respondents because they have responsibility for their firm's IS/IT processes and business and strategic decisions (Damanpour & Schneider, 2006). The sampling frame is determined based on the total number of SMEs in the selected population. Questionnaires will be sent to each SME registered with the Amman Chamber of Commerce (ACC). The standard and sophisticated statistical analysis, including multivariate regression, employs a recommended sample size where 200 is fair and 300 is good (Tabachnick & Fidell, 1996). Hair, Anderson, Tatham and Black (1998) suggest that a minimum of 20 observations is recommended (see also Talukder, 2014). To test a model, Hair, Anderson, Tatham and Black (1998) suggested a sample size of at least 200 because 200 is a 'critical sample size' that can be used for reliable results (Hoelter, 1983). However, an approach using the sample size of comparable and related current studies is suggested (Aaker, Benet-Martinez & Garolera, 2001) to achieve a sufficient reliability standard. For sufficient and more emphatic statistical power, a larger size may be required.

5.8 Sampling Population for the Study

The research population refers to the entire group of individuals, events, or things of interest that the researcher wishes to investigate (Sekaran & Bougie, 2019; Naseri, 2021). The study is for the advantage of the larger community but still, researchers cannot evaluate every person in the population due to the sampling techniques they adopted (Gravetter & Forzano, 2015). The primary reason for using sampling techniques is that testing everyone is costly and time-consuming, and actually impossible to do (Gravetter & Forzano, 2011). In the same context, Asiamah, Mensah and Oteng-Abayie (2017) write that a study population refers to a well-defined set of the same characteristics of individuals or items. In certain situations, all individuals or objects of a study population have the same features (Gravetter & Forzano, 2011). For example, top managers of SMEs comprise a collection of individuals in the SMEs population. According to Polit and Beck (2008) there are two kinds of population in the research field: the accessible population and the target population.

The accessible population is the aggregation of cases that meet the requirements specified and are available for analysis as subjects for study (Polit & Beck, 2008). A distinction between target and accessible communities often needs to be made. For example, the senior managers of SMEs in Jordan are the accessible population and available for analysis as subjects. Questionnaires will be sent to executive managers through cooperation with the Amman Chamber of Commerce, and a Survey Donkey link will be in the e-mail for the survey. Because the senior managers directly control the digital technologies adoption process, in most cases, the owner or manager is the same person (Ghobakhlooa & Ching, 2019). Information including a detailed description and aims of the research included in the e-mail in English and Arabic languages.

5.9 Sampling Size for the study

The research analysis aims to examine the sample and then generalize the findings to the larger population (Boddy, 2016). When doing quantitative research, the investigator uses a power analysis to identify the appropriate sample size for the study design and answer the research questions (Astroth & Chung, 2018). The precision of generalization depends on the sample's representativeness. In addition, how closely the sample represents the population is correlated with the degree of representativeness of a sample. Therefore, each researcher faces a challenge: obtaining the sample and what size will fully represent the population (Gravetter & Forzano, 2011; Walters, 2021). The sample size is a subset of a wider population that depicts the representatives of a given population accurately. It is argued that the larger the study, the more accurately the population represents it. However, there is a limit on the number of individuals or sample size used, considering the advantages of a greater sample size. The study was conducted using owners/ managers from registered ten categories SMEs in the capital of Jordan- Amman. These categories are: (a) Construction and building materials (b) Automotive-related repair maintenance & trades (c) Wholesale and retail trades (non- automotive (d) Finance and insurance. (e) Food & beverages (f) Agriculture (g) Information, communication & technology (h) Tourism (i) Real estate (j) Other services. A minimum of 20 measurements for each variable is recommended to study variance tests (Hair, Anderson, Tatham & Black, 1998). However, a larger size may be appropriate for reasonable and more emphatic statistical strength. Hair, Anderson, Tatham and Black (1998) propose there should be five observations for each independent variable. They state that the minimum ratio is 5 to 1, but the desired level is between 15 to 20 observations for each dependent and independent variable. Stevens (2012) suggested that for every predictor (independent variable) in the social sciences, 15 subjects are needed. Hence, this study includes 12 independent variables and 6 dependent variables. A sample of 300 to 400 respondents is required based on the suggestion for 15 to 20 observations on each dependent and independent variable to determine the sample size because this study uses 20 variables.

On a randomized basis, the target to about 1200-1600 SMEs to achieve a usable number of respondents (300-400). This can achieve a 25-30% response rate for generalizability purposes. It is necessary to expand the sample size to avoid poor response rates, which are frequent in most research addressing SMEs. Thus, the sample size that will be used here is significant. Data collection will be conducted through cooperation with the Amman Chamber of Commerce and other authorities dealing with SME issues. Some revisions to the wording, question sequence, and item layout will be done for the questionnaire before the final data collection and after the study pilot in both languages for more precision. Respondents will first be contacted by telephone or e-mail and informed about the research topic and its benefits before starting the survey.

5.10 Research Instrument for Study

Quantitative data for this research was collected using a questionnaire administered online to the respondents and the online communication criteria are documented in Table 5.3

Table 5.4 Questionnaire Communication online Methods

Criteria	Cost	Data collecti on- on	Ability to reach geographically dispersed regions	Questionna ire Length	Question Complexity	Anonymous Respondent	Rapport with respond ents	Resear cher bias	Need for the researcher. supervision	Response rate
Internet Online Questione rs	Very low	Fast	Very high Can reach globally	Long (4-12 pages)	Simple to moderate	possible	None	None	No	Moderate

Source: Adapted from Frazer and Lawley (2000).

The questionnaire items originated in other studies and were empirically tested and validated for this topic (Ghobakhoo & Ching, 2019; Won et al., 2020; Shahazad et al., 2020; Putra & Santoso, 2020; Dincă et al., 2020; Maroufkhani et al., 2020; Khayer et al., 2020; Abed, 2020). The instruments (questionnaires) collected information based on respondents' answeres about issues concerning digital technologies in Jordanian SMEs in and around Amman. The questionnaire will be constructed based on a five-point Likert-type scale (Likert, 1932): 1 = Strongly Disagree (SD), 2 = Disagree (D), 3 = Neutral (N), 4 = Agree (A), 5 = Strongly Agree (SA), because this scale produces better quality results than other scales (Revilla, Saris & Krosnick, 2014; Hassan, Zailani & Rahman, 2021).

5.11 Variables of the Study

The following are the determinants (independent variables) identified and discussed in the literature review influencing the adoption of digital technologies by SMEs. There are 20 variables in this study. As shown in Table 5.4, the 12 independent variables are: Technological context (technology strategy, employee's IT knowledge, technology infrastructure), organizational context (managerial support, training, reward system), socio-cultural context (peer support, social network, religion beliefs), and political-environment context (government support, government regulations, competitive pressure). Independent variables are the determinants of SMEs' perceptions of digital technologies, which consequently influences how they accept and implement them. The conceptual model also proposes the outcomes of this process. There are six outcome variables (performance, productivity, profitability, market share, customer satisfaction and sales improvement). Research questions with corresponding independent variables and dependent variables are shown in Table 5.4.

Table 5.5: Variables of the study

Research questions	**Independent variables**	**Dependent variables**

1. What is the impact of the critical technological, organizational, political-environmental, and socio-cultural determinants on SMEs' perceptions of digital technologies?	Technology strategy Employees' IT knowledge Technology infrastructure Managerial support Training, Reward system, Government support Government regulations Competitive pressure Peer support Social network Religion beliefs	SMEs' perceptions of digital technologies
2. What is the impact of demographic characteristics on SMEs' perceptions of digital technologies?	Gender Age Education Experience Industry Employees Role	
3. What is the impact of SMEs' perceptions of digital technologies on usage level?	SMEs' perceptions of digital technologies	Usage of digital technologies adoption
4. What are the expected benefits to Jordanian SMEs from using and adopting digital technologies?	Usage of digital technologies adoption	SMEs' performance SMEs' productivity SMEs' profitability Market share Customer satisfaction Sale improvement

5.12 Definitions of the Constructs and Measures of the Variables

The constructs measurement instrument (questionnaire) is based on previous validated measures. The questionnaire consists of five parts. The first part contains questions that seek to obtain demographic information on age, qualification, experience, employment experience, number of employees and role/position in the business. The list of questions is shown in Appendix 3. The first part of the questionnaire borrows from Mashal (2018), Putra and Santoso (2020), and Dincă, Dima and Rozsa (2019). Two other experts reviewed the questionnaire to ensure that the questions are relevant and logical. Before collecting data from a larger population, the questionnaire was piloted with 60 owner-managers of SMEs to ensure the survey is coherent as is the reliability of the constructs (Dwivedi et al., 2013; Kapoor, Dwivedi, Niall, Lal & Weerakkody, 2014). Following previous studies' arguments (Dwivedi, Kapoor, Williams, & Williams, 2013; Shareef, Dwivedi, Kumar, & Kumar, 2017), the draft version of the questionnaire was tested by three academics and three digital technology experts in SMEs. This study measured the demographic variables (age, qualification, experience, employment experience, number of employees and role in the business) using the method used in the literature (Chrisman & Patel, 2012; Oliveira et al., 2014; Easmon et al., 2019; Eller et al., 2020; Khayer et al., 2020; Lew & Sinkovics, 2013; Berghman et al., 2013; Ngah et al., 2017). The definitions for constructs and measurements of independent and dependent variables are provided below.

Adoption of digital technologies in SMEs

The diffusion of innovations (DOI) theory refers to a person's innovativeness, or how early he or she accepts new behaviors in comparison to other members of the social system or wider community (Haun et al., 2020). DOI theory claims that individuals do not immediately accept an innovation because some individuals are more likely than others to embrace it (Zhang & Nuttall, 2011). Based on other research (Raymond, 1985; Lee, 1986; Igbaria, Guimaraes & Davis, 1995; Igbaria, Zinatelli, Cragg & Cavaye, 1997; Al-Gahtani & King, 1999; Talukder, 2014), five indicators measure usage of digital technologies via Artificial Intelligence (AI). They are as follows:

1) The actual amount of time spent:

The participants were asked to specify the amount of time they spent (hours per week) using AI in their SMEs. Answers will be on a five-point Likert scale ranging from “less than 1 hour” to “more than 5 hours”.

On average, how frequently do you use digital technologies-AI in the workplace?

2) Frequency of use:

The participants were asked about the average frequency of their digital technologies-AI usage, which will be measured on a five-point Likert scale ranging from “once each week" or to several times a day".

On average, how much time do you spent each week using digital technologies-AI in your job?

3) Level of usage:

AI usage level will provide comprehensive information on the overall adoption and activities done. Participants were asked to identify their level of usage on a five-point Likert scale ranging from "not used at all" to "used extensively."

Can you please indicate the level of usage of digital technologies-AI?

4) The number of Used Features:

The respondents were asked to describe how many features they used, on a five-point Likert scale ranging from “none" to various features used".

How many different types of digital technologies-AI do you use?

5) The sophistication level of features used:

The digital technologies such as AI have several advanced features and sophistication levels. The participants were asked to specify how many sophisticated features they had utilized, giving their answers on a five-point Likert scale ranging from 1 "not used" to “using extensively".

Do you use the sophisticated features of digital technologies-AI?

Technology strategy

Technological strategy is adapted from Kearns and Sabherwal (2006), Lyver and Lu (2018), Zahra (1996), Eller et al. (2020), and Wielgos, Homburg and Kuehnl (2021). To what extent do you agree that the following are objectives of your organization’s technology strategy? The following questions were asked:

1) Our digital strategy accelerates new product and service launches.
2) Our digital strategy takes advantage of data, information, and knowledge.
3) Our digital strategy opens up entirely new chances to create value for our clients.
4) My company use licensing agreements extensively to use AI.
5) My company use joint ventures for AI research and development.

Employees' IT Knowledge

The items here are based on the work done by Thong and Yap (1995), Lin and Lin (2008), Musteen et al. (2017), Eller et al. (2020), and Zaman, Goldberg, Kelly, Russell and Drye (2021). Moreover, the following questions were thought out:

1) I learned from my previous work knowledge to use AI.
2) I learned from my prior training programs how to use AI.
3) I have learned to use AI in my previous job.
4) I learned from previous experience with similar new technology.
5) I am already familiar with a similar new technology system.

Technology infrastructure

Technology infrastructure items are based on several studies, such as those by Zhu and Kraemer (2005), Bhatt et al. (2010), Bhatt and Grover (2005), Lyver and Lu (2018), and Hasan, Ali, Kurnia and Thurasamy (2021). Here are the relevant questions:

1) Technology infrastructure of my company is good.
2) Technology infrastructure of my company can meet its business needs.
3) Technology infrastructure of my company enables us to cooperate with all stakeholders.
4) Technology infrastructure of my company is adequate.
5) Technology infrastructure of my company can support all processes.

Managerial Support

Measurements of managerial support include evaluating management's encouragement of AI in the workplace and the resources for ensuring it works properly. Participants will be asked to indicate the scope of agreement or disagreement with the following five statements. The items are adopted from studies by: Igbaria, Parasurman and Baroudi (1996); Igbaria, Zinatelli, Cragg and Cavaye (1997); Tarofder, Marthandan and Haque (2010); Taluker (2014); Frisk and Bannister (2017), Chung and Kuo (2018); Radović-Marković, Tomaš-Miskin and Marković (2019); Agostini and Nosella (2020); Chege and Wang (2020); and Abed (2020). These items are:

1) Management is aware of the benefits that can be attained with the use of AI.

2) Management always encourages employees to use AI in their work.
3) Management is providing different support to AI adoption.
4) Management is keen to make sure that employees are using AI.
5) Management provides most of the essential help and resources to use AI.

Training

Measurement of training will be assessed by getting respondents to evaluate the extent of training provided to employees in Jordanian SMEs. The training were assessed based on five criteria, based on work by Kotey and Folker (2007), Igbaria, Zinatelli, Cragg and Cavaye (1997), Taukder (2014), Musteen, Ahsan and Park (2017), Selvarajah, Le and Sukunesan (2019), Garzoni, Turi, Secundo and Del Vecchio (2020), and Zaman, Goldberg, Kelly, Russell and Drye (2021). These are as follows:

1) My company provides training for employees to explain the features of AI.
2) My company is offering training sessions to improve AI usage.
3) My company is offering guidance for employees on how to use AI.
4) My company is offering specialized instructions regarding AI usage.
5) My company is offering a specific person for individualized assistance when employees encounter difficulties in using AI.

Reward System

The reward system or incentives will be measured as individuals' beliefs regarding the benefits or consequences of embracing innovation (Talukder, 2014). According to Kerr and Newell (2003) and Isik (2004), a positive relationship between rewards system/incentives and technology adoption is evident. Individuals are more likely to be motivated not because they like to perform tasks but because there are rewards attached (Fishbein & Ajzen, 1974; Seun et al., 2017). Participants were asked to rate perceived benefits of using AI. Items are taken from Igbaria, Zinatelli, Cragg and Cavaye (1997), Chang and Cheung (2001), Gallagher and Muehlegger (2011), Adler (2013), and Syed- Ikhsan and Rowland (2004):

1) AI applications assist me to save time in work.
2) AI applications assist me to accomplish tasks more quickly.
3) Using AI applications improves my productivity.

4) Using AI applications keeps my private data more secure.
5) Using AI applications gives me flexibility in my work.

Government support

Measuring government support requires evaluating how senior management allocates appropriate resources for accessing AI. Based on Tan and Teo (2000), Khan (2011), and Al-Khouri (2012a), Mikalef, Lemmer, Schaefer, Ylinen, Fjørtoft, Torvatn, Gupta and Niehaves (2021) the following five statements will be responded to:

1) Government encourages using AI applications.
2) Government facilities are available to use AI applications.
3) Government promotes AI applications.
4) Government adopts an assertive policy to use AI applications.
5) Government supports encourage firms to use AI in their business.

Government regulations

Government regulations refer to legislative processes and systems for how, when, and why Internet should be used in the workplace. Respondents were asked about the government regulations or laws that assist them. Five items, based on studies by Li (2008), Luken and Van Rompaey (2008), Agrawal and Wu (2015), Gupta and Barua (2016), Al-Khouri (2012b), Maroufkhani et al. (2020), and Mikalef, Lemmer, Schaefer, Ylinen, Fjørtoft, Torvatn, Gupta and Niehaves (2021) were employed. The questions to be asked are as follows:

1) Government establishes regulations in relation to AI usage.
2) Government regulations are significant for AI adoption.
3) Government policies encourage individuals to use AI applications.
4) Country’s legal system supports the adoption of AI applications.
5) Government regulations help individuals to use AI applications.

Competitive pressure

Competitive pressure items are based on the studies by Thong (1999), Al-Qirim and Corbitt (2002), and AlBar and Hoque (2019). Respondents were asked to consider the following five statements:

1) My company is under pressure from competitors to adopt AI for our business.
2) Business competitors encourage us to implement AI applications.
3) My company would adopt AI in response to what competitors are doing.
4) AI would give my company a stronger competitive advantage.
5) What competitors do will significantly impact our decision to use AI.

Peer Support

Peer support evaluation will be measured by the impact, inspiration, and support offered by peers to an individual employee. Top managers were asked to show on a five-item scale the level of agreement or disagreement with the five statements about the power, motivation, and encouragement shown by peers. Five items are based on the work by Lewis, Agarwal and Sambamurthy (2003), Talukder et al. (2014), and Alsheddi, Sharma and Talukder (2020):

1) I learned how to use AI effectively from my friends.
2) Communicating with my friends assists me to learn AI.
3) Opinions of people in informal groups to which I belong are significant to me to use AI.
4) Observing my friends performing similiter task using AI increased my intention to use it.
5) People in informal groups to which I belong think using AI is valuable.

Social Network

This refers to the extent to which people influence employees in a similar discipline or other organizations. The social network was measured by the five-item scale below. Five items were adopted from Lewis, Agarwal and Sambamurthy (2003), Talukder et al. (2019), and Alsheddi, Sharma, and Talukder (2020). They are presented as follows:

1) I use AI because my relevant organization also uses AI.

2) I use AI because my friends in another firm are using AI.
3) I use AI as other people use a similar system.
4) People in my discipline think that AI usage is valuable.
5) The opinions of people in my discipline are important on the issue of AI.

Religious beliefs

Religious beliefs were measured by asking respondents questions about how the adoption of AI reflects their faith or religious beliefs. Measurement was based on Roof, Bocarnea, and Winston (2017), Schaefer and Gorsuch (1993), Underwood (2006), and Alsheddi, Sharma, and Talukder (2020). The respondents will be asked to respond to the following five statements:

1) My religion does not discourage the adoption of AI.
2) My religious opinion is optimistic about using AI.
3) My religion motivated me to use AI.
4) My religion gives me energy while using AI.
5) My religion enhances my caring for others and sharing knowledge about AI.

SMEs' perceptions of digital technologies

Perception refers to the conscious reception, selection, processing, and interpretation of information by individuals, which is a function of behavioral beliefs and assessment outcomes (Talukder, 2014). Attitude refers to a construct that reflects a person's level of like or dislike related to an item. The participants will be asked to rate five items according to how they feel regarding using the AI on a five-point Likert scale. The items are adopted from Lam, Cho and Qu (2007), Putzer and Park (2010), Lin (2011), Talukder (2014), and Zaman, Goldberg, Kelly, Russell and Drye (2021). These items have been modified, as follows:

1) Using AI applications is important to my work.
2) Using AI applications is relevant to my work duties.
3) Using AI applications is helpful.
4) Using AI applications is practical.
5) I like the idea of using AI applications.

SMEs’ Performance

SMEs’ performance is a formative measure guided by routines/procedures, sales or customer satisfaction performance and operational efficiency. For this research, SME performance refers to how SMEs perceive that using digital technology will improve their functioning. Measuring SME performance is based on Venkatraman and Ramanujam (1986), Wu et al. (2006), Khin and Ho (2018), Bouwman, Nikou and de Reuver (2019), Qalati et al. (2021), and Zulu-Chisanga, Chabala and Mandawa-Bray (2020). These items have been modified as follows:

1) AI helps my company to perform much better than competitors about profitability as a percentage of sales.
2) AI helps company to perform much better than competitors for return on investment.
3) AI helps my company to perform much better than competitors concerning cash flow from operations.
4) AI helps my company to reach the financial goals.
5) AI helps my company to improve its brand visibility and reputation.

SMEs’ Productivity

Technologies contribute to productivity in SMEs (Naushad & Sulphey, 2020). Productivity is measured by the value of time spent using human, capital, and natural resources (Porter et al., 2008). For this research, productivity refers to the extent to which SMEs perceive that using AI will help them work better and identify new markets (Medina, 2011). Measurement items are adopted from the work published by Raguseo and Vitari (2018), Maroufkhani et al. (2020) and Qalati et al. (2021). The items are as follows:

1) Using AI improves work motivation.
2) Using AI able me to preform my tasks easier.
3) Using AI reduce the time I spent on unproductive activities.
4) Using AI increase the quality at my job output.
5) Using AI improves fluidity of work.

SMEs’ Profitability

Naushad and Sulphey (2020) stated that the benefits of ICT could lead to good profitability and sales, and care for customers. For this research, profitability refers to how SMEs perceive that using the Internet will raise their profits. Measurement items are taken from Santos and Brito (2012) and Tarutė and Gatautis (2014):

1) AI helps my company to have good returns on assets,
2) AI helps my company to have good returns on investment,
3) AI helps my company to have good net income/revenues,
4) AI helps my company to have good returns on equity,
5) AI helps my company to have good added economic value.

Customers' satisfaction

Customers' satisfaction refers to using the Internet to help clients get what they want and ensuring they are served well. Items here are adapted from Narver and Slater (1990), Chan (2012), Venkatesh et al. (2012), Akkucuk (2014) and Ali Qalati et al. (2020):

1) AI helps my company to have close contact with customers.
2) AI allows my company to have good communication with customers.
3) AI assists my company to develop a good understanding of customers.
4) AI enables my company to build strong relationships with customers.
5) Our customers are more loyal to my company because of AI.

Market share

The percentage of sales a company has in a specific market or industry is known as market share (Roseline & Valerie, 2020). Gaining or increasing market share is a strategy for improving a company's market/industry position and value (Sarkissian, 2010). Market share items are adapted from Wu, Mahajan and Balasubramanian (2003), Kim, Cavusgil and Calantone (2006), and Roseline and Valerie (2020) and written here:

1) AI assists my company to attain good market positioning.
2) AI helps us to be percentage share is higher.
3) AI assists my company to attract more customers.

4) AI assists us to be service efficiency is commendable.
5) AI assists my company to Alignment with market demands.

Sales Improvement

Sales improvement outcomes refer to digital technologies enhancing sales. Items here are derived from Wu, Mahajan and Balasubramanian (2003), Kim, Cavusgil and Calantone (2006), and Rahayu and Day (2017):

1) The sales volume of our products has increased by using AI.
2) The prices of our products have changed after using AI applications.
3) The number of new customers that we are able to acquire has increased.
4) The number of existing customers that we are able to retain has increased
5) My firm sells more than its competitors after using AI.

5.13 Validity and Reliability of the Study

Validity and reliability are the two main requirements for a good research instrument (Hair, Anderson, Tatham & Black, 1998; Talukder, 2014). Key measurements will be used to determine the validity and reliability of this study. According to Hair, Anderson, Tatham and Black (1998), validity is the degree to which a measurement correctly reflects what should be measured. Validity is linked to the accuracy of the research outcomes. The model developed here is based on already established models and theories and the items in the questionnaire were adopted from previous research. The relevant information is shown below in Table 5.5.

Table 5.6: Participants in various studies on SMEs

Studies	Participants
Lyver and Lu (2018)	SME Management team
Medina et al. (2011)	SME General managers
Gavrila and de Lucas Ancillo (2021)	SME Management
Lin (2014)	SME Senior Managers

Khayer et al. (2020)	SME owners/CEOs
Putra et al. (2020)	SME owners/managers
Bi et al. (2017)	SME founder or CEO
Ghobakhlooa and Ching (2019)	SME CEOs or owners and executive managers
Moh'd Anwer (2019)	SME senior executives and IT managers
Mubarak et al. (2019)	SME managerial level

The language should be as straightforward as possible for respondents when they answer a questionnaire. The questions follow well-established patterns that helped to underpin the questionnaire's validity. According to Hair et al. (1998) and Talukder (2014), reliability refers to a metric when identical outcomes are obtained over time and through various contexts. Reliability is expressed numerically and generally as a coefficient: a higher coefficient indicates high reliability, and Cronbach's alpha is the most frequently used tool to measure it (Ahmad & Ahmad, 2018). Steps will be taken to ensure that any measurement represents what it was planned to measure, and it is free of any systematic error or bias. Several tests, such as expert opinions, data analysis, pilot study and reporting of the reliability coefficient, will be undertaken to ensure the study's reliability.

5.14 The pilot study

Pilot studies are preliminary, small-scale analyses conducted to ensure that the main objectives of a more extensive and subsequent study are achieved (Ahmad & Ahmad, 2018). The pilot or feasibility study enables the researcher to make any adjustments to the research methods, such as the wording of questions so they make sense and are not ambiguous, and the study's objectives can be achieved convincingly (Ahmad & Ahmad, 2018; Eldridge, Lancaster, Campbell, Thabane, Hopewell, Coleman & Bond, 2016). The questionnaire created for this research has been made keeping in mind the recent changes that have happened in the SME sector in Jordan and distributed among owners and/or managers by email. Respondents were asked to complete the questionnaire and return it to the researcher within seven days. The findings served to check if there are any problems or discrepancies in the research process. If any such issues emerge then the questionnaire can be changed. The pilot study tested the questionnaire's validity and assessed whether the instructions and questions were clear and understandable and can be answered in good time (Md-Sidin, Sambasivan & Ismail, 2010; Fiksenbaum, 2013). The pilot study involved 60 SME owners/managers.

5.15 Data Collection Procedures

Data was collected through a questionnaire posted as an online survey to recruit participants. Questionnaires are a standard method for gathering data (De Vaus, 2002). The research online survey questionnaire will be the primary procedure for obtaining data, and SMEs' managers in Amman were asked to answer it. Table 5.3 summarizes the advantages of online questionnaires. Items in the questionnaire were developed, modified, and adopted using previously tested items. The questionnaire was distributed to respondents by e-mail and their email addresses were obtained from the Amman Chamber of Commerce database (Amman Chamber of Commerce, 2022). Both digital adopters and non-adopters of digital technologies in SMEs were invited to take part in this survey. Their views on various aspects were explored for technological characteristics and organizational, political-environmental and socio-cultural contexts of their respective firms. Approval from the human research ethics committee at University of Canberra was before the study commenced with questionnaires sent in May 2022. Respondents were sent a reminder twice, one week after the online survey questionnaires had been distributed and another reminder after two weeks. In the questionnaire's introduction, the SMEs owners/managers were advised it would take 25-30-minute to complete. All data collection procedures took place from May 2022 to July 2022. However, the researcher expected some delays because of the public and school holidays during this period, and possible interruptions due to the ongoing COVID-19 pandemic.

5.16 Data Analysis

This study analyzed the data using the IBM Statistical Package for Social Sciences (SPSS version 27), especially concerning measurement validity and reliability (Cronbach's alpha). This research employed multivariate statistical approaches for the correlations between many variables—descriptive statistical procedures. Correlations, Factor Analysis and multiple regression analysis (MRA) were carried out to connect groups within the same category and the variances between them. The research carried out frequency distribution and used the cumulative percentage as a descriptive method. At the same time, the percentage shows the rate of adoption. The respondent’s profiles were outlined via descriptive methods, while the percentages reflected the digital technologies’ adoption rate. Correlation matrices, internal reliability analyses, linearity tests performed, as was an examination of the assumptions. The model for this study was tested using MRA on the collected data, given that Hair, Anderson, Tatham and Black (1998) stated that it can evaluate the relationship between a single dependent variable (criterion) and several independent variables (predictor).

For the correlations between a vast number of variables, multivariate statistical approaches are used (Boonkaewwan, Sonthiphand & Chotpantarat, 2021). Talukder (2014) contends that regression analysis is a way to evaluate the predictive power of several independent variables (Dielman, 2005). The relative significance of each independent variable and the form of relationship in predicting the dependent measure was established in the study. Each independent variable's relative value was determined when making this simultaneous evaluation (Hair, Anderson, Tatham & Black, 1998; Talukder, 2014). Multiple regression analysis offers an insight into the relationship between independent variables in their prediction of the dependent variable; it is necessary to check these interrelationships because correlations between independent variables can make certain variables redundant in the predictive effort (Talukder, 2014). The multicollinearity problem (if any) will be found by identifying the level of collinearity and degree to which it affects the estimated coefficients.

An examination of the correlation matrix for independent variables is the simple and most effective way of identifying collinearity. The presence of high correlations (generally .90 and above) is the initial indication of substantial collinearity (Hair, Anderson, Tatham & Black, 1998, p. 191). The linearity of the relationship between the dependent and independent variables representing the degree to which the shift in the dependent variable is correlated with the independent variable will be discussed in this analysis. The analysis will choose a method to determine the regression model in predicting the dependent variable through the statistical significance of the overall model (Dielman, 2005; Hair, Anderson, Tatham & Black, 1998). This study examined R-square, which is the coefficient of correlation, also known as the determination coefficient. The R-square value indicates the percentage of the total variance of dependent variables described by independent variables. The study employed analysis of variance (ANOVA), regression coefficient. These analyses demonstrated the relative significance and contribution of the technological, organizational, political-environmental, and socio-cultural contexts for digital technologies adoption in Jordan. This method is also effective when the model is complex, with multiple latent variables and moderating variables, and even with smaller samples (Hair Hult, Ringle & Sarstedt, 2021; Alqudah, Amran & Hassan, 2019; Alshirah, Lutfi, Alshirah, Saad, Ibrahim, & Mohammed, 2021). All analyses were aimed to examine the conceptual model developed here and extended previous research by examining multiple sets of variables in AI adoption in Jordanian SMEs, including outcome variables.

5.17 Ethical Considerations

The researcher acknowledged the advice and directions given by supervisors at the University of Canberra. Before data collection commenced, permission from the University of Canberra's ethics committee was acquired as per university regulations. Participation was voluntary and all survey participants were assured of their personal confidentiality of their anwers and privacy concerns. All survey data was maintained in both the researcher's secured filing cabinet and on a password-protected computer, to which no-one else had access. An ethical researcher must be mindful of the goals of validity and reliability, be context-sensitive, honest and 'upfront 'about his/her own interests. Anonymity is very important to participants in research and must be respected. Data obtained in this research will be retained for the period specified in the policy on data retention according to the university's archiving policy.

5.18 Conclusion

This chapter provided a very detailed overview of the methodological method, including a description of the research philosophy, research design, quantitative study, study sampling frame, sampling population, sample size, research instrument, variables of the study, and measures of the constructs. The data were collected through an online survey questionnaire distributed to 1600 SMEs' owners/ managers in the capital of Jordan, Amman. The Survey Monkey system served to collect the online data. In order to detect and correct any issues and mistakes, the survey questionnaires were pretested using a pilot project. Data was analyzed using SPSS version 27 statistical software. The descriptive analyses were done, including correlations multiple regressions, frequencies cross-tabulations and ANOVA tests. Tests were done to find any multicollinearity problems and the linearity of relationships Finally, the determinants that affect SMEs' adoption of digital technologies were reported and the integrity of the conceptual model developed in this study was tested. The nest chapter introduces statistical analysis and discusses the quantitative data and results.

CHAPTER SIX: RESULTS AND DISCUSSION

6.1 Introduction

The objective of this chapter is to provide a systematic analysis of the data collected from the owners/managers of Jordanian SMEs in Amman. This chapter examines the data that emerged from the answers to the questionnaire survey. First, the determinants influencing SMEs to adopt digital technologies are discussed, along with the impacts of respondents' demographic characteristics, specifically gender, age, academic qualification, experience, industry classifications, number of employees, and role in the business. Next, this chapter discusses the cross-tabulation of demographics with digital technology usage levels. Then the chapter tests the instruments' reliability, factor loading, and correlation analyses. This is followed by regression analyses and checks of the assumptions. Finally, it discusses the hypotheses' results, followed by a summary and conclusion.

6.2 The Questionnaire

Surveys have made much progress over the past decade thanks to innovative technologies, and especially when gathering online data (Ochoa & Revilla, 2022; Tiene, 2000). The owners/managers of SMEs were invited via email to participate in the survey devised for this study. The survey was conducted between May and July 2022 and the questionnaire comprised eight sections. In addition, the respondents' demographic characteristics were categorized better to understand the sample (Sekaran, 2003). Consequently, the first section contains seven questions about the demographic characteristics of those taking part, namely gender, age, academic qualification, employment experience, industry classification, number of employees, and role in the business. The second section contains five questions about the usage of AI applications, while the third comprises 15 statements about the technological context divided into five groups. This is followed by a fourth section containing 15 statements about the organizational context, divided into five groups. The fifth section consists of 15 statements about the political–environmental context divided into five groups, while the sixth contains 15 statements about the socio-cultural context divided into five groups. The seventh group consists of 30 statements about the expected benefits, divided into six groups. Lastly, the eighth consists of 5 statements about the respondents' perceptions. It appears that the online survey is very low-cost, is fast to collect, and can reach widely dispersed regions (Frazer & Lawley, 2000). Also, the main strengths of the electronic survey tools are confidentiality, free expression, and fairness of the responses (Davis, 2000).

The total number of owners/managers who received the questionnaire was 1600 SMEs in the capital of Jordan, Amman. After one week, a reminder was again sent by email, encouraging the managers to respond to the questionnaire. The number of those who did so was 401, which produced a response rate of 25 %. Shamuddiha (2005) stated that the number of organizational studies in a developing country is generally small, and 20% could be very optimistic so this response rate is considered sufficient. The researcher discarded answers that were missing in any returned questionnaire. Before starting the analysis, it is essential to define and treat any missing data, such as incomplete answers or missing parts of the questionnaire. Out of the 401 questionnaire answers collected, 37 were considered unusable because they had missing response items. After eliminating these 37 responses, the remaining 364 constituted the study sample.

6.3 Analysis the Demographic Information of the respondents

Demographic variables shape individual beliefs and attitudes regarding digital technologies (Chawla & Joshi, 2021). This section discusses the respondents' demographic data and it was evaluated in terms of descriptive and frequency analysis. Descriptive data constitute an essential source of information about SMEs' acceptance of digital technologies in Jordan. Demographic data collected from the questionnaire provided information on the personnel and organizational characteristics of the respondents. Table 6.1 summarizes the 364 respondents' demographic details concerning gender, age, academic qualification, employment experience, industry classification, number of employees, and role/position in the business.

Table 6.1 Demographic Information of the respondents

Categories	Criteria	Frequency	Percentage
Gender	Male	256	70.3%
	Female	108	29.7%
Age	20-29	55	15.1%
	30-39	67	18.4%
	40-49	76	20.9%
	50-59	97	26.6%
	>=60	69	19.0%
Academic Qualification	Primary	12	3.3%
	HSC	34	9.3%
	Bachelor	188	51.6%
	Master’s degree	90	24.7%
	PhD	40	11.0%
Employment Experience	1-2 year	11	3.0%
	2-3 year	52	14.3%
	3-4 year	75	20.6%
	4 -5 year	169	46.4%
	>=5 years	57	15.7
Industry Classification	Construction and building material.	29	8.0%
	Automotive-related repair maintenance & traded.	12	3.3%
	Wholesale and retail trade (non-automotive).	38	10.4%
	Finance and insurance.	44	12.1%
	Food & beverage.	24	6.6%
	Agriculture	11	3.0%
	Information, communication	102	28.0%
	Tourism	5	1.4%
	Real estate	11	3.0%
	Other services	88	24.2
Number of Employees	Non	10	2.7%
	1-4 employees	27	7.4%
	5-19 employees	49	13.5%
	20-99 employees	207	56.9%
	99-25 employees	71	19.5%
Role in the Business	Business owner	101	27.7%
	Director	38	10.4%
	Senior Manager	57	15.7%
	Manager	111	30.5%
	Supervisor	57	15.7%
	Total	**364**	**100%**

Gender

Gender influences how SMEs owners and managers respond to and use new technology (Eze, Awa, Chinedu-Eze & Bello, 2021). Gender is an essential variable that can determine people’s acceptance and adoption of digital technologies in Jordan. Subsequently, information concerning gender is presented in Table 6.2. In terms of the participants' gender, the results revealed significant difference between males and females was evident. There were slightly more male respondents (70.3%) than female respondents (29.7%). The SME sector in Jordan has more men than women and noticeably, female managers in the capital of Jordan amounted to nearly 30%. The age of the respondents does stand out as significant when considering people's views about specific issues. Generally, age demonstrates a person's cognitive level of development and what they consider to be important responses to questions. According to the World Bank, the population of Jordan was estimated to be around 10.2 million in 2020, with approximately half of the population being female (World Bank, 2021). Traditionally, Jordanian culture has strongly emphasised gender roles, with men being viewed as the primary breadwinners and women expected to focus on domestic responsibilities. However, in recent years, there have been efforts to promote gender equality and increase women's participation in the workforce. As a result, women in Jordan increasingly participate in the force and contribute to various sectors, including transportation, public service, and governance (Al-Ma'aitah & Al-Sarayreh, 2020). Despite these gains, significant gender disparities persist, particularly in terms of pay and career advancement opportunities. There is still work to ensure that women in Jordan have equal opportunities and can fully participate in the economy and society (Al-Ma'aitah & Al-Sarayreh, 2020; Al-Rababa'h, 2017).

Table 6.2: Participants' gender distribution

Gender	Frequency	Percentage
Female	108	29.7%
Male	256	70.3%
Total	364	100.0%

Age groups

Age does affect new technology adoption in a developing country (Hubona, 2007). Figure 6.2 and Table 6.3 illustrate the age groups of the respondents, in which most were 50-59 years of age (26.6%), 20.9% at 40-49, 18.4% at 30-39, 15.1% at 20-29, 19.0% at 60 and above (60). An interesting feature of these statistics is that those young up to the age of 50 are shouldering the responsibility of accepting digital technologies in Jordanian SMEs. It appears that the 20-49 cohort consists of 54.4% and they are working as owners/managers in SMEsr. Table 6.3 and Figure 6.2 below represent the age groups of this study.

Table 6.3: Participants' age distribution

Gender	Frequency	Percentage
20-29.	55	15.1
30-39.	67	18.4
40-49.	76	20.9
50-59.	97	26.6
60 and above (60)	69	19.0
Total	364	100%

Academic qualifications

Education or academic level is one of the most significant characteristics that might affect individuals' attitudes to digital technologies and other social trends. Managers and employees who are early adopters of innovations have a higher education level and are more knowledgeable about technology (Ho & Lim, 2018). People's responses are likely to be determined by their level of academic qualifications. In terms of academic qualifications as shown in Table 6.4 and Figure 6.3, the findings showed that most respondents had a Bachelor's degree (51.6%), followed by a Master's degree (24.7%), while approximately 9.3% of respondents had a higher school certificate and 11.0% had a PhD and only 3.3% finished primary school. However, it can be concluded from Figure 6.3 above that generally the respondents had a higher education qualification, which is considered critically important today to create a knowledge-based society. The variable 'academic qualifications' was investigated. The data pertaining to education is presented in Table 6.4 and Figure 6.3.

Table 6.4: Participants' Academic qualifications distribution

Academic qualifications	Frequency	Percentage
Primary school	12	3.3
High school (Year 12)	34	9.3
Bachelor	188	51.6

Master's degree	90	24.7
PhD	40	11.0
Total	364	100%

Employment Experience

Management's lack of experience and knowledge of IT capabilities deter adoption in the workplace (Huang & Rust, 2018). Figure 6.5 and Table 6.4 illustrate the employment experience of the respondents, in which most were 4-5 years (46.4%), followed by: the 3-4 years (20.6%); 5 years or more (15.7%); 2-3 years (14.3%) and 1-2 years (3.0%). The data about employment experience is presented in Table 6.5 and Figure 6.4.

Table 6.5: Participants' Employment Experience distribution

Employment Experience	Frequency	Percentage
1-2 years	11	3.0
2-3 years	52	14.3
3-4 years	75	20.6
4 -5 years	169	46.4
5 years or more	57	15.7
Total	364	100.0%

Industry Classification

The type of industry as a demographic variable addresses performance variance that may arise due to industry-specific environments and market competition conditions (Oliveira, Thomas & Espadanal, 2014). Figure 6.5 and Table 6.6 summarize the industry classification of the respondents, in which most were in Communication & technology 28.0% followed other services 24.2%, Finance and insurance 12.1%, Wholesale and retail trade (non-automotive) 10.4%, Construction and building materials 8.0%, Food & beverages 6.6%, Automotive-related repair maintenance & trades 3.3%, Real estate, 3.0%, Agriculture 3.0%, and Tourism 1.4%.

Table 6.6: Participants' Industry Classification distribution

Industry Classification	Frequency	Percentage
Construction and building materials	29	8.0

Automotive-related repair maintenance & trades	12	3.3
Wholesale and retail trade (non-automotive)	38	10.4
Finance and insurance	44	12.1
Food & beverages	24	6.6
Agriculture	11	3.0
Information, communication & technology	102	28.0
Tourism	5	1.4
Real estate	11	3.0
Other services	88	24.2
Total	364	100.0

Number of Employees

The most common measure of business size is the number of employees (Tsai & Hung, 2016; Heredia, Castillo-Vergara, Geldes, Gamarra, Flores & Heredia, 2022). Table 6.7 and Figure 6.6 show that most of participants had 20-99 employees (56.9%), 99-250 employees (19.5%) followed 5-19 employees (13.5%), while 1-4 employees (7.4%) but no employees just the owner only (2.7%) of respondents. The data about the number of employees are presented in Table 6.7 and Figure 6.6.

Table 6.7: Number of Employees distribution

Number of Employees	Frequency	Percentage
None	10	2.7%
1-4 employees	27	7.4%
5-19 employees	49	13.5%
20-99 employees	207	56.9%
99-250 employees	71	19.5%
Total	364	100.0%

Role in the Business

A firm's management plays a crucial role in organizational changes that implement the technology (Agi & Jha, 2022). In this study, concerning the role or position in the business, the analysis shows that mid-level managers amounted to 30.5%, followed by 27.7% who were business owners, while 15.7% were both supervisors and senior managers. A total of 114 respondents for both roles and directors was evident (10.4%). The data about role in the business is presented in Table 6.8 and Figure 6.7.

Table 6.8: Participants' Role in the Business distribution

Position in Business	Frequency	Percentage
Business owner	101	27.7%
Director	38	10.4%
Senior Manager	57	15.7%
Mid-level Manager	111	30.5%
Supervisor	57	15.7%
Total	364	100.0%

6.4 Usage of Artificial Intelligence (AI) applications

Managers or supervisors may find it helpful to employ AI applications that are measurable, attainable, explicit, relevant, and tractable when creating objectives and assignments for personnel to complete. This section includes items that confirm employee utilization in terms of frequency, time spent, features accessible, and several applications of AI. The following tables summarize the information gathered from respondents and show that respondents use AI in various ways, ranging from never to many times each day.

Time spent per week using Artificial Intelligence for workplace duties

Table 6.9 displays the time spent per week using Artificial Intelligence (AI) for workplace duties in SMEs. The results revealed that respondents were active users of AI. The time spent per week on using AI applications indicates that 61 respondents (16.8%) spent less than 1 hour per week, 70 respondents (19.2%) spent 1–2 hours per week, 73 respondents (20.1%) spent 2–3 hours per week, 70 respondents (19.2%) spent 3–4 hours per week, and the highest percentage which was 90 respondents (24.7%) spent more than 5 hours per week on AI.

Table 6.9: Time spent per week using AI applications for workplace duties.

Usage Time	Frequency	Percentage (%)
Less than 1 hour	61	16.8%
1–2 hours	70	19.2%
2–3 hours	73	20.1%
3–4 hours	70	19.2%
More than 5 hours	90	24.7%
Total	364	100%

Frequency of use of Artificial Intelligence (AI) in job-related activities

Generally, managers and employees work together to plan, monitor, and review the workplace objectives and their overall contributions. Table 6.10 summarizes the frequency of using AI in job-related activities. Data analysis for usage levels shows that 42 respondents (11.5%) used AI less than once a month, whereas 60 respondents (16.5%) used AI once a month, 81 respondents (22.3%) a few times each month, 85 respondents (23.4%) about once a day. A total of 96 respondents 26.4% used AI several times a day.

Table 6.10: Frequency of using AI in job-related activities.

Frequency of Usage	Frequency	Percentage (%)
Less than once a month	42	11.5%
Once a month	60	16.5%
few times a month	81	22.3%
Once a day	85	23.4%
Several times a day	96	26.3%
Total	364	100%

Usage Level of Artificial Intelligence in job-related activities

Artificial Intelligence (AI) in workplace duties can improve efficiency and productivity. However, according to the analysis of the answers to the question regarding the level of usage of AI in employees' daily work, 26 respondents (7.1%) had not used AI for any purpose, whereas 109 respondents (29.9%) used AI rarely, 75 respondents (20.6%) used AI quite often, 115 respondents (31.6%) used AI frequently and 39 respondents (10.7%) used AI extensively. Table 6.11 shows the data regarding the level of usage of AI in the workplace.

Table 6.11: Usage Level of Artificial Intelligence (AI) in workplace duties

Level of Usage	Frequency	Percentage (%)
Not used at all	26	7.1
Used rarely	109	29.9
Used quite often	75	20.6
Used frequently	115	31.6
Used extensively	39	10.7
Total	364	100%

Different types of Artificial Intelligence (AI) applications used

The analysis shows that different types of AI are used by employees. According to Table 6.12, 17 respondents (4.7%) did not use any applications, whereas 151 respondents (41.5%) used 1–2 AI applications, 102 respondents (28.0%) used 2–3 applications, 57 respondents (15.7%) used 3–4 applications, and 37 respondents (10.2%) used 5 or more AI applications for their daily workplace duties.

Table 6.12: Different types of Artificial Intelligence (AI) applications

Usage Application	Frequency	Percentage (%)
None	17	4.7%
1-2	151	41.5%
2-3	102	28.0%
3-4	57	15.7%
5 and above	37	10.2%
Total	364	100.0%

Usage of advanced features of Artificial Intelligence

The results in Table 6.13 indicate that 12.1% of 44 respondents have not used the advanced features of AI, whereas 34.6% only used them rarely, and 26.4% of 96 respondents used advanced features quite often. 18.7% used advanced features frequently while 8.2% used advanced features extensively.

Table 6 13: Usage of advanced features on Artificial Intelligence (AI)

Usage Features	Frequency	Percentage (%)
Not used at all	44	12.1
Used rarely	126	34.6
Used quite often	96	26.4
Used frequently	68	18.7
Used extensively	30	8.2
Total	364	100.0

6.5 Cross-Tabulation for Level of Usage by Demographics

The cross-tabulation of the analysis shows the level of usage as measured by time spent per week using AI for work purposes, frequency of using AI, level of usage of AI, how many different types of AI are used, and advanced features used according to respondents' gender, age, qualification, employment experience, industry classification, number of employees and position in business. This provides important information on how SMEs' managers/owners deploy AI applications.

Cross-Tabulation by Gender

Cross-tabulation (gender by time)

Table 6.14 presents the cross-tabulation analysis for the usage period of AI by male and female respondents. Results show that the respondents who most actively used AI (for more than 4 hours a week) were male (18.7%), while female respondents (6.1%) used AI for more than 4 hours a week. In terms of usage duration for 3-4 hours per day, the percentage of female respondents is 6.5% compared to males (12.6%). The percentage of female respondents (6.1%) indicated their use of AI was only 2–3 hours per week, and for male respondents at 14.1% it was 2-3 hours per week. In terms of usage duration of 1–2 hours, more female respondents

(6.5%) intended to use AI for that length of time, followed by male participants (12.6%). Meanwhile 6.1% of females used AI less than 1 hour per week and male 10.7% used it for less than 1 hour per week. It appears that both male and female consisted of 90 respondents with (24.8%) use AI more than 4 hours per week.

Table 6.14: Cross-tabulation (gender by time)

Gender	**Time**					**Total**
	Less than 1 hour	hour 1–2	hours 2–3	hours 3–4	More than 4 hours	
Female	22	24	22	18	22	108
	6.1%	6.5%	6.1%	4.9%	6.1%	29.7%
Male	39	46	51	52	68	256
	10.7%	12.6%	14.1%	14.2%	18.7%	70.3%
Total	61	70	73	70	90	364
	16.8%	19.1%	20.2%	19.1%	24.8%	100.0%

Cross-tabulation (gender by frequency)

In Table 6.15 the results display the frequency of usage of AI by both males and females. The highest percentage refers to male respondents (21.7%) who use AI several times on a daily basis. Similarly, the percentage of female respondents (4.7%) indicated that they use AI several times a day as well. The lowest percentages show that 16 female respondents (4.4) used AI less than once, while 26 male respondents (7.1%) used AI less than. The rates show that female respondents (6.6%) used AI once a day, while male respondents (16.8%) used AI once a day. Moreover, the analysis identified that 25 (6.9%) female respondents used AI applications a few times a month, while (15.4%) 56 male respondents used AI infrequently or a few times a month. Both male and female respondents (94, 16.4%) utilised AI once a month.

Table 6.15: Cross-tabulation (gender by frequency)

Gender	**Frequency**					**Total**
	Less than once a month A	Once a month	few times a month	Once a day	Several times a day	
Female	16	26	25	24	17	108
	4.4	7.1%	6.9%	6.6%	4.7%	29.7%
Male	26	34	56	61	79	256

	7.1%	9.3%	15.4%	16.8%	21.7%	70.3%
Total	42	60	81	85	96	364
	11.5%	16.4%	22.3%	23.4%	26.4%	100.0%

Cross-tabulation (gender by usage)

Table 6.16 below cross-tabulates the usage of AI according to gender. Specifically, 29 (8.0%) female respondents and 86 (23.6%) male respondents frequently used AI. A total of 9 (2.5%) for males and 30 (8.2%) females both used the AI extensively consist of both (9.6%), while 26 (7.2%) females used AI quite often. In total 49 (13.5%) males used AI quite often. However, a total of 109 (29.9%) participants used AI used rarely, while 26 (7.1%) respondents did not use AI at all in their duties.

Table 6.16: Cross-tabulation (gender by Usage Level)

Gender	**Usage**					**Total**
	Not used at all Used	Used rarely	Used quite often	frequently Used	extensively	
Female	12	32	26	29	9	108
	3.3%	8.7%	7.2%	8.0%	2.5%	29.7%
Male	14	77	49	86	30	256
	3.8%	21.2%	13.5%	23.6%	8.2%	70,3%
Total	26	109	75	115	39	364
	7.1%	29.9%	20.7%	31.6%	10.7%	100.0%

Cross-tabulation (gender by application)

Table 6.17 presents the cross-tabulation results for gender regarding different types of AI application usage. Based on the survey, data showed that 29.1% of male respondents used 1–2 types of AI applications, 12.4% of female participants used 1–2 types, while 9.1% female and 19.0% male both used 2-3 types of AI. Only 7 respondents (1.9%) of female and 30 respondents or (8.2%) of males used 5 above types of AI. 8 respondents (2.2%) of female and 9 (2.5%) of male respondents did not use any types of AI at all. However, a total of 57 respondents who were 15.6 % of the participants used 3-4 types of AI for their work.

Table 6.17: Cross-tabulation (gender by application)

Gender	Application					Total
	None	1–2	2–3	3–4	5 & above	
Female	8	45	33	15	7	108
	2.2%	12.4%	9.1%	4.1%	1.9%	29.7%
Male	9	106	69	42	30	256
	2.5%	29.1%	19.0%	11.5%	8.2%	70.3%
Total	17	151	102	57	37	364
	4.7%	41.5%	28.1%	15.6%	10.1%	100.0%

Cross-tabulation (gender by features)

Table 6.18 presents the cross-tabulation results for gender regarding features of AI application usage. Findings show that 2.8% of female respondents and 5.5% of male respondents used the features of AI extensively. Table 6.13 reveals that 2.8% of female and 8.5% of male respondents used the features of AI frequently. Meanwhile 126 (34.5%) respondents of males and females rarely used the features of AI and 96 (26.3%) respondents used AI features quite often. However, a total of 44 (12.1%) participants did not use any features of AI. The analysis shows that male respondents used various features of AI more often than females.

Table 6.18: Cross-tabulation (gender by features)

Gender	Features					Total
	Not used at all	Used rarely	Used quite often	Used frequently	Used extensively	
Female	13	44	31	10	10	108
	3.6%	12.0%	8.5%	2.8%	2.8%	29.7%
Male	31	82	65	58	20	256
	8.5%	22.5%	17.8%	16.0%	5.5%	70,3%
Total	44	126	96	68	30	364
	12.1%	34.5%	26.3%	18.8%	8.3%	100.0%

Cross-Tabulation by Age

Cross-tabulation (age by time)

The results of the cross-tabulation for age are presented in Table 6.19 below. It reveals that the majority of respondents are in the 50-59 age group, while the minority are in the 20-29 age group. The percentage of those respondents who use the AI applications 5 and above are: 7.2% for the age group 50-59, 4.4% for the age group 40-49, 3.8% for the age group 30-39, 3.3% for the age group 20-29, 6.0% for the 60 and older group. The total percentage of all respondents who use the AI applications 5 and over hours per day is 24.7%. The percentage of those respondents who use the AI applications 3-4 hours are: 3.0% for the age group 20-29, 3.3% for the age group 30-39, 3.3% for the age group 40-49, 5.5% for the age group 50-59, 4.1% for the age group 60 and over group. The percentage of those respondents who use the AI applications 2 to 3 hours per day are: 4.1 for the age group 20-29, 2.5 for the age group 30-39,4.7% for the age group 40-49, 5.2% for the age group 50-59, 3.6% for the age group 60 and over group.

Meanwhile the percentage of respondents who use the AI applications 2 to 3 hours per day is 20.1%. The percentage of those respondents who use the AI applications 1 to 2 hours per day are: 2.7% for the age group 20-29, 4.1% for the age group 30-39, 4.7% for the age group 40-49, 4.8% for the age group 50-59, 3.0% for the age group 60 and over group. The total percentage of all respondents who use the AI applications 1 to 2 hours per day is 19.3%. Lastly, regarding the respondents who use the AI applications for less than one hour per day are: 1.9% for the age group 20-29, 4.7% for the age group 30-39, 3.8% for the age group 40-49, 4.1% for the age group 50-59, 2.2% for the age group 60 and over group. The total percentage of 61 respondents who use the AI applications for less than hours per day is 16.7%.

Table 6.19: Cross-tabulation (age by time)

Age	**Times**					Total
	than 1 hour	1-2 hours	2-3 hours	3-4 hours	More than 5 hours	
20-29.	7	10	15	11	12	55
	1.9%	2.7%	4.1%	3.0%	3.3%	15.0%
30-39.	17	15	9	12	14	67
	4.7%	4.1%	2.5%	3.3%	3.8%	18.4%
40-49.	14	17	17	12	16	76
	3.8%	4.7%	4.7%	3.3%	4.4%	20.9%

50-59	15	17	19	20	26	97
	4.1%	4.8%	5.2%	5.5%	7.2%	26.8%
60 and above	8	11	13	15	22	69
	2.2%	3.0%	3.6%	4.1%	6.0%	18.9%
Total	61	70	73	70	90	364
	16.7%	19.3%	20.1%	19.2%	24.7%	100.0%

Cross-tabulation (age by frequency)

Table 6.20 presents the results of the cross-tabulation for age by frequency. The percentage of those respondents who use the AI applications several times a day is 4.7% for the age group 20-29, 4.1% for the age group 30-39, 4.1% for the age group 40-49, 8.3% for the age group 50-59, 5.3% for the age group 60 and over the group. The total percentage of all respondents who use AI applications several times a day is 26.4%, which reveals that most all-age respondents use AI applications several times a day. Meanwhile, for who, those respondents who use the AI applications once a day are: 2.2% for the age group 20-29, 5.3% for the age group 30-39, 6.0% for the age group 40-49, 6.0% for the age group 50-59, 3.8% for the age group 60 and over the group. The total percentage of all respondents who use the AI applications daily is 23.4%. The percentage of those respondents who use the AI applications a few times a month is 2.8% for the age group 20-29, 2.5% for the age group 30-39, 4.9% for the age group 40-49, 6.0% for the age group 50-59, 6.0% for the age group 60 and over the group. The total percentage of all respondents who use the AI applications a few times a month is 22.3%. The percentage of those respondents who use the AI applications once a month is: 3.6% for the age group 20-29, 3.9% for the age group 30-39, 3.0% for the age group 40-49, 3.6% for the age group 50-59, 2.5% for the age group 60 and over the group. The total percentage of all respondents who use the AI applications once a month is 16.5%. The percentage of those respondents who use the AI applications for less than once a month is 1.9% for the age group 20-29, 2.7% for the age group 30-39, 2.7% for the age group 40-49, 2.7% for the age group 50-59, 1.4% for the age group 60 and over the group. The total percentage of all respondents who use AI applications for less than once a month is 11.4%. The results indicate that 50-59 age group people used AI applications more frequently than young respondents. Notably, the respondents of age 50-59 (97, 26.6%) use AI applications.

Table 6.20: Cross-tabulation (age by frequency)

Age	Frequency					Total
	Less than once a month	Once a month	A few times a month	Once a day	Several times a day	
20-29	7	13	10	8	17	55
	1.9%	3.6%	2.8%	2.2%	4.7%	15.2%
30-39	10	14	9	19	15	67
	2.7%	3.9%	2.5%	5.3%	4.1%	18.5%
40-49	10	11	18	22	15	76
	2.7%	3.0%	4.9%	6.0%	4.1%	20.7%
50-59	10	13	22	22	30	97
	2.7%	3.6%	6.0%	6.0%	8.3%	26.6%
60 and above	5	9	22	14	19	69
	1.4	2.5%	6.0%	3.8%	5.3%	19.0%
Total	42	60	81	85	96	364
	11.4%	16.5%	22.3%	23.4%	26.4%	100.0%

Cross-tabulation (age by usage)

Table 6.21, Figure 6.8 shows the cross-tabulation analysis for age groups according to usage of AI applications. The percentage of those respondents who use the AI applications used extensively for 1.1% the age group 20-29, 0.8% for the age group 30-39, 1.7% for the age group 40-49, 4.1% for the age group 50-59, 3.0% for the age group 60 and over the group. The total percentage of all respondents who use AI applications used extensively is 10.7%. The percentage of those respondents of age 20-29 used AI frequently is 5.2%, while 5.2% for the age group 30-39, 4.9% for the age group 40-49, 9.9% for the age group 50-59, 6.4% for the age group 60 and over the group. The total percentage of 115 respondents who use AI applications used AI frequently is 31,6%. The percentage of those respondents of age 20-29 used AI quite often is 3.0%. While 4.4% for the age group 30-39, 5.2% for the age group 40-49, 3.9% for the age group 50-59, 4.1% for the age group 60 and over the group. The total percentage of all respondents who use AI applications used AI quite often is 20.6%. The percentage of those respondents of age 20-29 used AI rarely is 4.4%. While 5.5% for the age group 30-39, 7.7% for the age group 40-49, 7.7% for the age group 50-59, 4.6% for the age group 60 and over the group. The total percentage of all respondents who use AI applications used AI rarely is 29.9%. The percentage of those respondents of age 20-29 not used at all is

1.4%. While 2.5% for the age group 30-39, 1.4% for the age group 40-49, 1.1%% for the age group 50-59, 0.8% for the age group 60 and over the group. The total percentage of all respondents who use AI applications not used AI at all is 7.2%. Importantly, it appears that the group of all age who not used AI at all is the lowest respondents.

Table 6.21: Cross-tabulation (age by usage)

Age	Usage					Total
	Not used at all	Used rarely	Used quite often	Used frequently	Used extensively	
20-29	5	16	11	19	4	55
	1.4	4.4%	3.0%	5.2%	1.1%	15.1%
30-39	9	20	16	19	3	67
	2.5%	5.5%	4.4%	5.2%	0.8%	18.4%
40-49	5	28	19	18	6	76
	1.4	7.7%	5.2%	4.9%	1.7%	20.9%
50-59	4	28	14	36	15	97
	1.1%	7.7%	3.9%	9.9%	4.1%	26.6%
60 and above	3	17	15	23	11	69
	0.8%	4.6%	4.1%	6.4%	3.0%	18.9%
Total	26	109	75	115	39	364
	7.2%	29.9%	20.6%	31.6%	10.7%	100.0%

Cross-tabulation (age by application)

The results for cross-tabulation of age by AI application, as displayed in Table 6.22, show the numbers of different AI applications that the other age groups use in Jordanian SMEs. The 35 respondents in the 60 and above age groups demonstrate that an average of 9.6% used 1–2 different types of applications. The 40-49 age group displays 8.5% of the 31 respondents used 1-2 applications. 7.7% of 28 respondents the 30-39 used 1-2 AI applications. While a percentage of 4.7% of 17 respondents the aged 20-29 and 11.0% of 44 respondents of the aged from 50-59 used 1-2 AI applications. The total percentage of151 respondents who used (1-2) AI applications is 41.5%. The 2-3 AI applications become the second percentage used in all age categories. The total percentage of respondents who used (2-3) AI applications is 28.0%. The total percentage of respondents who used (3-4) AI applications is 15.6%. Lastly, 5 AI applications above used only 10.2% of all age categories, the number of respondents was only 30 respondents and from age 40- 60 and above used 5 AI applications. Age from 30-39 only 3 respondents and 4 respondents age from 20-29. Furthermore, only 4.7% of 17 the respondents for all age did not use any application and ignored AI applications altogether. From the results of the 364 respondents, it appears that the total highest percentage (41.5%) of 151 respondents used from 1-2 application.

Table 6.22: Cross-tabulation (age by application)

Age (In Years)	**Application (Time of Usage)**					**Total**
	None	1-2	2-3	3-4	5 & above	
20-29	4	17	16	14	4	55
	1.1%	4.7%	4.4%	3.8%	1.1%	15.1%
30-39	8	28	21	7	3	67
	2.2%	7.7%	5.8%	1.9%	0.8%	18.4%
40-49	2	31	25	8	10	76
	0.5%	8.5%	6.9%	2.2%	2.8%	20.9%
50-59	2	40	27	18	10	97
	0.5%	11.0%	7.4%	5.0%	2.8%	26.7%
60 and above	1	35	13	10	10	69
	0.2%	9.6%	3.5%	2.8%	2.8%	18.9%
Total	17	151	102	57	37	364
	4.7%	41.5%	28%	15.6%	10.2%	100.0%

Cross-tabulation (age by features)

Table 6.23 summarises the cross-tabulation of respondents' age by advanced AI features. The outcomes confirmed that the respondents rarely use advanced AI features in all age categories of respondents who rarely used AI applications is 34.6%, It is the highest percentage of all respondents. In the meantime, the percentage for the 6.4% age 60 and above, 7.2% in age (50-59), 8.0% in age (40-49), 7.7% in age (30-39) and 5.5% in age (20-29). Of the 44 respondents who did not use AI features at all, 12.0%. Meanwhile, the percentage for the 1.4% age 60 and above, 3.0% in age (50-59), 3.3% in age (40-49), 2.7% in age (30-39) and 1.7% in age (20-29) did not use AI features at all. For the percentage of the respondents who use AI applications quite often, it is 5.0%. for the age 60 and above, 6.4%, in age group (50-59), 5.5% in age group (40-49), 4.1% in age group (30-39) and 5.5% in age group (20-29). Meanwhile, the percentage of 96 respondents who use AI applications quite often is 26.4%. Results also indicate that 18.7% of the respondents from all age categories used the AI applications frequently. In the meantime, the percentage for the 5.0% age 60 and above, 6.7% in age group (50-59), 3.0% in age group (40-49), 2.5% in age group (30-39) and 1.9% in age group (20-29). While the results for advanced AI feature usage are extensive for the respondents in all age categories, the lowest percentage is 8.3% In the meantime, the percentage for the 1.4% age 60 and above, 3.9% in age group (50-59), 1.1% in age group (40-49), 1.4% in age group (30-39) and 0.5% in age group (20-29).

Table 6.23: Cross-tabulation (age by features)

Age (In Years)	**Features (Time of Usage)**					**Total**
	Not used at all	Rarely Used	Quite often	Used frequently	Used extensively	
20-29	6	20	20	7	2	55
	1.7%	5.5%	5.5%	1.9%	0.5%	15.1%
30-39	10	28	15	9	5	67
	2.7%	7.7%	4.1%	2.5%	1.4%	18.4%
40-49	12	29	20	11	4	76
	3.3%	8.0%	5.5%	3.0%	1.1%	20.9%
50-59	11	26	23	23	14	97
	3.0%	7.2%	6.4%	6.4%	3.9%	26.6%
60 and above	5	23	18	18	5	69
	1.4%	6.4%	5.0%	5.0%	1.4%	18.9%
Total	44	126	96	68	30	364
	12.0%	34.6%	26.4%	18.7%	8.3%	100.0%

Cross-tabulation by Academic Qualifications

Cross-tabulation (Academic qualifications status by time)

The results regarding the cross-tabulation for academic qualifications status by time are presented in Table 6.24. The results indicate that the 188 respondents who had bachelor's degrees used AI applications at various times as the highest percentage it is 51.6%, compared with 3.3% of respondents who had a primary school, 9.4%% who had a high school degree, 24.7% who had a master's degree and 11% who had PhD. Results also indicate that 16.8%of the respondents from all qualifications categories used the AI applications for less than 1 hour. In the meantime, the percentage for 0.5% who qualified with a PhD, 5.8% with a master's degree, 8.0% with a bachelor's degree, and 1.7% with Higher School Certificate (HSC). 0.8%

who studied primary school. The percentage of respondents who used AI applications from 1-2 hours indicates that 19.2% were from all age categories. bIn the meantime, the percentage for the 2.5% who qualified with a PhD, 3.8% with a master's degree, 20.4% with a bachelor's degree, and 1.9% with Higher School Certificate (HSC). 0.5% who qualified with primary school. The respondents who used AI applications from (2-3) hours indicated that 20.1%were from all age categories. While the percentage of 3.0% who qualified with a PhD, 4.1% with a master's degree, 11.0% with a bachelor's degree, and 1.7% with a High School Certificate (HSC). 0.3%who qualified with primary school. The percentage of respondents who used AI applications from (3-4) hours indicate that 19.2%were from all age categories. The percentage for 2.2%who qualified with a PhD, 5.8% with a master's degree, 9.6% with a bachelor's degree, 1.4% with Higher School Certificate (HSC) and 0.3% who got primary school. Lastly. The respondents who used AI applications from 5 hours and more indicated that 24.7% were from all age categories. In the meantime, the percentage for 2.8% who qualified with a PhD, 5.2% with a master's degree, 12.6% with a bachelor's degree, 2.7% with a high school certificate (HSC) and the percentage of 5 respondents consisting of 1.4% who studied primary school.

Table 6.24: Cross-tabulation (Academic qualifications level by time).

Academic Qualifications	Time					Total
	Less than 1 hour	1-2 hours	2-3 hours	3-4 hours	More than 5 hours	
Primary School	3	2	1	1	5	12
	0.8%	0.5%	0.3%	0.3%	1.4%	3.3%
Higher School Certificate (HSC)	6	7	6	5	10	34
	1.7%	1.9%	1.7%	1.4%	2.7%	9.4%
Bachelor's degree	29	38	40	35	46	188
	8.0%	20.4%	11.0%	9.6%	12.6%	51.6%
Master's degree	21	14	15	21	19	90
	5.8%	3.8%	4.1%	5.8%	5.2%	24.7%
PhD	2	9	11	8	10	40
	0.5%	2.5%	3.0%	2.2%	2.8%	11.0%
Total	61	70	73	70	90	364
	16.8%	19.2%	20.1%	19.2%	24.7%	100%

Cross-tabulation (academic qualifications by frequency)

The results concerning the cross-tabulation for academic qualifications status by frequency are presented in Table 6.25. for the respondents who use the AI applications several times a day, the percentages are 1.1% for those primary School, 1.7% for those with high school certificates. 15.4% for those with bachelor's degrees, 5.2% for those with a master's degree 3.0%for those with a PhD. The total percentage of all respondents who use the AI application several times a day is 26.4%. Respondents who employ the AI applications once a day are 0.6% for those with primary school, 1.4% for high school certificates. 11.3% for those with bachelor's degrees and 6.9% for those with master's degrees. 3.3% for those who PhD. The total percentage of all respondents who use the AI application once a day a day is 23.4%. The results for those respondents who employ the AI applications a few times a month based on the percentages are: 0.8% for those in Primary School, 2.2% for those with high school certificates. 12.6% for those with bachelor's degrees and 4.4% for those with master's degrees. 2.2% for those who PhD. The total percentage of all respondents who use the AI application a few times a month is 22.2%. Respondents who employ the AI applications once a month are: 0.3% for those in primary school and 2.2% for those with High School certificates (HSC). 6.9% for those with bachelor's degrees and 5.2% for those with master's degrees. 1.9% for those who PhD.

The total percentage of all respondents who use the AI application once a month is 16.5%. The results for respondents who employ the AI applications for less than once a month based on the percentages are 0.6%% for those in Primary School and 1.9% for those with a high school certificate. 5.5% for those with bachelor's degrees and 3.0% for those with master's degrees. 0.6% for those who PhD. The total percentage of all respondents who use the AI application less than once a month is 11.5%. The results show that 15.4% of 56 respondents with a bachelor's degree used AI applications several times a day as the highest. In contrast, the total percentage of those with a bachelor's degree used AI applications. The results show that respondents with primary education qualifications used AI applications for less than all other education levels. The total percentage of 12 respondents' those who used in different times AI applications with primary education qualifications is 3.3% only.

Table 6.25: Cross-tabulation (academic Qualifications level by frequency)

Academic Qualifications	Frequency					Total
	less than once a month	once a month	a few times a month	once a day	several times a day	
Primary School	2	1	3	2	4	12
	0.6%	0.3%	0.8%	0.6%	1.1%	3.3%
High School Certificate (HSC)	7	8	8	5	6	34
	1.9%	2.2%	2.2%	1.4%	1.7%	9.4%
Bachelor's degree	20	25	46	41	56	188
	5.5%	6.9%	12.6%	11.3%	15.4%	51.6%
Master's degree	11	19	16	25	19	90
	3.0%	5.2%	4.4%	6.9%	5.2%	24.7%
PhD	2	7	8	12	11	40
	0.6%	1.9%	2.2%	3.3%	3.0%	11.0%
Total	42	60	81	85	96	364
	11.5%	16.5%	22.2%	23.4%	26.4	100%

Cross-tabulation (academic qualifications by usage)

The results concerning the cross-tabulation for academic qualifications status by usage are presented in Table 6.26 and Figure 6.9. for the respondents who use the AI applications extensively, the percentages are 0.6% for those primary School, 1.1% for those with high school certificates. 6.3% for those with bachelor's degrees, 0.8% for those with a master's degrees 1.9% for those with a PhD. The total percentage of all respondents who use the AI application several times a day is 10.7%. Respondents who employ the AI applications used frequently are 0.3% for those with primary school, 1.7% for high school certificates. 16.7% for those with bachelor's degrees and 8.8% for those with master's degrees. 4.1% for those who PhD. The total percentage of all respondents who use the AI application several times a day is 31.6%. The results for those respondents who employ the AI applications Used quite often based on the percentages are: 0.6% for those in primary school, 0.6% for those with high school certificates. 10.2% for those with bachelor's degrees and 8.0% for those with master's degrees. 1.4% for those who PhD. The total percentage of all respondents who use the AI application used quite often is 20.6%. Respondents who employ the AI applications used rarely: 1.1% for those in primary school and 4.4% for those with high school certificates. 16.6% for those with bachelor's degrees and 6.0% for those with master's degrees. 2.8% for those who PhD. The total percentage of all respondents who use the AI application once a month is 29.9%. The results for respondents who employ the AI applications not used at all based on the percentages are 0.8% for those in primary school and 1.7% for those with a high school certificate. 2.8% for those with bachelor's degrees and 1.1% for those with master's degrees. 0.8% for those who PhD. The total percentage of all respondents who use the AI application less than once a month is 7.2%. The results of the cross-tabulation analysis for academic qualifications by usage show that respondents with a bachelor's degree used AI applications frequently more than those respondents who did not go on to higher education and the percentage are 16.7% bachelor's degree, 8.8% master's degree and 4.1% PhD.

Table 6.26: Cross-tabulation (academic Qualifications by usage)

Academic	**Usage**					**Total**
	Not used at all	Used rarely	Used quite often	Used frequently	Used extensively	
Primary School	3	4	2	1	2	12
	0.8%	1.1%	0.6%	0.3%	0.6%	3.3%
Higher School Certificate	6	16	2	6	4	34
	1.7%	4.4%	0.6%	1.7%	1.1%	9.4%
Bachelor's degree	10	57	37	61	23	188
	2.8%	16.6%	10.2%	16.7%	6.3%	51.6%
Master's degree	4	22	29	32	3	90
	1.1%	6.0%	8.0%	8.8%	0.8%	24.7%
PhD	3	10	5	15	7	40
	0.8%	2.8%	1.4%	4.1%	1.9%	11.0%
Total	26	109	75	115	39	364
	7.2%	29.9%	20.6%	31.6%	10.7%	100%

Cross-tabulation (Academic qualifications by types of the AI applications)

The results concerning the cross-tabulation for academic qualifications status by the types are presented in Table 6.27. for the respondents who use the AI applications for more than 5 hours, the percentages are 0.0% for those who with primary school means no one used the AI applications and 0.0% for those with high school certificates. 0.6% for those with bachelor's degrees, 2.5% for those with master's degrees 1.1% for those with a PhD. The total percentage of all respondents who use the AI application for more than 5 hours is 10.2%. Of the respondents who used the AI applications for 3-4 hours, 0.6% for those in primary school and 1.4% for those with high school certificates. 7.1% for those with bachelor's degrees, 3.5% for those with master's degrees 3.0% for those with a PhD. The total percentage of all respondents who use the AI application for 3-4 hours is 15.6%. While the respondents who used the AI applications for 2-3 hours, the percentages are 1.1% for those in primary school, no one used the AI applications, and 3.0% for those with high school certificates. 13.2% for those with bachelor's degrees, 7.1% for those with master's degrees 3.6% for those with a PhD. The total percentage of all respondents who use the AI application for 2-3 hours is 28%. In the meantime, for the respondents who used the AI applications for 1-2 hours, 1.4% for those in primary school, meaning no one used the AI applications, and 3.3% for those with high school certificates. 23.9% for those with bachelor's degrees, 9.9% for those with master's degrees 3.0% for those with a PhD. The total percentage of all respondents who use the AI application for 1-2 hours is 41.5%. Results show that respondents with bachelor's degrees are the highest users of AI applications in their workplace compared with any other education level – that is, 23.9.% Are bachelor's degree holders who use 1–2 applications per day. In the meantime, for the respondents who used the AI applications for less than one hour, 0.3% for those in primary school, and 1.1% for those with high school certificates. 1.4% for those with bachelor's degrees, 1.6% for those with master's degrees 0.3% for those with a PhD. The total percentage of all respondents who use the AI application for less than one hours is 4.7% only.

Table 6.27: Cross-tabulation (academic Qualifications by application)

Academic	**Applications**					**Total**
	Less than 1 hour	1-2 hours	2-3 hours	3-4 hours	More than 5 hours	
Primary School	1	5	4	2	0	12
	0.3%	1.4%	1.1%	0.6%	0	3.3%
Higher School Certificate (HSC)	4	12	11	5	2	34
	1.1%	3.3%	3.0%	1.4%	0.6%	9.4%
Bachelor's degree	5	87	48	26	22	188
	1.4%	23.9%	13.2%	7.1%	6.0%	51.6%
Master's degree	6	36	26	13	9	90
	1.6%	9.9%	7.1%	3.5%	2.5%	24.7%
PhD	1	11	13	11	4	40
	0.3%	3.0%	3.6%	3.0%	1.1%	11.0%
Total	17	151	102	57	37	364
	4.7%	41.5%	28%	15.6%	10.2%	100%

Cross-tabulation (academic qualifications by advanced features)

The results concerning the cross-tabulation for academic qualifications status by more than one features on the AI applications are presented in Table 6.28. for the respondents who use the AI applications extensively, the percentages are 0.3% for those primary School, 0.6% for those with high school certificates. 5.2% for those with bachelor's degrees, 16.0% for those with a master's degrees 0.6% for those with a PhD. The total percentage of all respondents who use the AI application at all times is 8.3%. Respondents who employ the AI applications used frequently are 0.6% for those with primary school, 1.6% for high school certificates. 8.8% for those with bachelor's degrees and 3.5% for those with master's degrees. 4.1% for those who PhD. The total percentage of all respondents who use the AI applications frequently is 18.7%. The results for those respondents who employ the AI applications used quite often based on the percentages are: 0.3% for those in primary school, 2.2%bfor those with high school certificates. 13.2% for those with bachelor's degrees and 7.4% for those with master's degrees. 3.3% for those who PhD. The total percentage of all respondents who use the AI application used quite often is 26.4%. Respondents who employ the AI applications used rarely: 1.9% for those in primary school and 2.5% for those with high school certificates. 19.5% for those with bachelor's degrees and 8.5% for those with master's degrees. 2.2% for those who PhD. The total percentage of all respondents who use the AI application rarely is 34.6%. The results for respondents who employ the AI applications not used at all based on the percentages are 0.3% for those in primary school and 2.5% for those with a high school certificate. 4.5% for those with bachelor's degrees and 3.5% for those with master's degrees. 0.8% for those who PhD. The total percentage of all respondents who do not use at all the AI application is 12.0%. Respondents with bachelor's degrees used a more than one features of AI applications significantly more than any of the other groups. Also, respondents with bachelor's degrees, master's degrees and PhD used advanced features frequently compared with respondents with other educational levels.

Table 6.28: Cross-tabulation (academic level by features)

Academic	**Features**					**Total**
	Not used at all	Used rarely	Used quite often	Used frequently	Used extensively	

Primary School	1	7	1	2	1	12
	0.3%	1.9%	0.3%	0.6%	0.3%	3.3%
Higher School Certificate	9	9	8	6	2	34
	2.5%	2.5%	2.2%	1.6%	0.6%	9.4%
Bachelor's degree	18	71	48	32	19	188
	4.5%	19.5%	13.2%	8.8%	5.2%	51.6%
Master's degree	13	31	27	13	6	90
	3.5%	8.5%	7.4%	3.5%	1.6%	24.7%
PhD	3	8	12	15	2	40
	0.8%	2.2%	3.3%	4.1%	0.6%	11.0%
Total	44	126	96	68	30	364
	12.0%	34.6%	26.4%	18.7%	8.3%	100%

Cross-Tabulation by Experience of Employees

Cross-tabulation (experience of employees by time)

The results of the cross-tabulation for experience of employees by time are presented in Table 6.29 below. reveals that the majority of respondents about experience of employees from 4 -5 years who are used AI applications more than 4 hours, while the minority are about experience of employees who work about 1–2-year hours per week. The percentage of those respondents who use the AI applications more than 4 hours are: 0.3%for who has 1–2-year experience, 4.1% for employees who has the 2–3-year experience, 5.0% for 3–4-year experience, 10.7% for employees who 4 -5-year experience, 4.7% for employees who 5 year or more experience. The total percentage of all industry respondents who use the AI applications more than 4 hours per week is 24.8%. The percentage of those respondents who use the AI applications more than 3-4 hours are: 0.0% for who has 1–2-year experience, 2.7% for employees who has the 2–3-year experience, 3.8% for 3–4-year experience, 9.5% for employees who 4 -5-year experience, 3.0% for employees who 5 year or more experience. The total percentage of all industry respondents who use the AI applications more than 4 hours per week is 19.2%. The percentage of those respondents who use the AI applications from 2-3 hours are: 1.1% for who has 1–2-year experience, 2.2% for employees who has the 2–3-year experience, 3.0% for 3–4-year experience, 10.2% for employees who 4 -5-year experience, 3.5% for employees who 5 year or more experience. The total percentage of all industry respondents who use the AI applications from 2-3 per week is 20%. The percentage of those respondents who use the AI applications more than 1-2 hours are: 0.6% for who has 1–2-year experience, 2.2% for employees who has the 2–3-year experience, 4.1% for 3–4-year experience, 9.3% for employees who 4 -5-year experience, 3.0%for employees who 5 year or more experience. The total percentage of all industry respondents who use the AI applications 1-2 is 19.2%. The percentage of those respondents who use the AI applications for less than 1 hour are: 1.1%for who has 1–2-year experience, 3.0% for employees who has the 2–3-year experience, 4.7% for 3–4-year experience, 6.6% for employees who 4 -5-year experience, 1.4% for employees who 5 year or more experience. The total percentage of all industry respondents who use the AI applications for less than 1 hour is 16.8%.

Table 6.29: Cross-tabulation (experience of employees by time)

Employment Experience	**Time**					**Total**
	Less than 1 hour	1-2 hours	2-3 hours	3-4 hours	(More than 4 hours	
1-2 year	4	2	4	0	1	11
	1.1%	0.6%	1.1%	0	0.3%	3.0%
2-3 year	11	8	8	10	15	52
	3.0%	2.2%	2.2%	2.7%	4.1%	14.3%
3-4 year	17	15	11	14	18	75
	4.7%	4.1%	3.0%	3.8%	5.0%	20.6%
4 -5 year	24	34	37	35	39	169
	6.6%	9.3%	10.2%	9.5%	10.7%	46.4%
5 year or more.	5	11	13	11	17	57
	1.4%	3.0%	3.5%	3.0%	4.7%	15.7%
Total	61	70	73	70	90	364
	16.8%	19.2%	20%	19.2%	24.8%	100.0%

Cross-tabulation (experience of employees by Frequently)

The results of the cross-tabulation for experience of employees by Frequently are presented in Table 6.30 below. reveals that the majority of respondents about experience of who are used AI applications several times a day, while the minority are about experience of employees who work less than once a month. The percentage of those respondents who use the AI applications several times a day are: 0.3% for who has 1–2-year experience, 4.7% for employees who has the 2–3-year experience, 4.5% for 3–4-year experience, 12.0% for employees who 4 -5-year experience, 4.4% for employees who has 5 year or more experience. The total percentage of all industry respondents who use the AI applications more than 4 hours per week is 26.4%. The percentage of those respondents who use the AI applications once a day are: 1.1% for who has

1–2-year experience, 1.9% for employees who has the 2–3-year experience, 4.4% for 3–4-year experience, 12.0% for employees who 4 -5-year experience, 3.8% for employees who 5 year or more experience. The total percentage of all industry respondents who use the AI applications once a day is 23.4%. The percentage of those respondents who use the AI applications a few times a month are: 0.3% for who has 1–2-year experience, 1.9% for employees who has the 2–3-year experience, 5.2% for 3–4-year experience, 9.9% for employees who 4 -5-year experience, 4.5% for employees who has 5 year or more experience. The total percentage of all industry respondents who use the AI applications a few times a month is 22.2%. The percentage of those respondents who use the AI applications once a month are: 0.3% for who has 1–2-year experience, 3.3% for employees who has the 2–3-year experience, 2.7% for 3–4-year experience, 8.5% for employees who 4 -5-year experience, 1.6% for employees who has 5 year or more experience. The total percentage of all industry respondents who use the AI applications once a month is 16.5%. The percentage of those respondents who use the AI applications for less than once a month are: 1.1% for who has 1–2-year experience, 2.5% for employees who has the 2–3-year experience, 3.3% for 3–4-year experience, 3.8% for employees who 4 -5-year experience, 0.8%for employees who has 5 year or more experience. The total percentage of all industry respondents who use the AI applications for less than once a month is 11.5%.

Table 6.30: Cross-tabulation (experience of employees by Frequently)

Employment Experience	**Frequently**					**Total**
	less than once a month	once a month	a few times a month	once a day	several times a day	
1-2 year	4	1	1	4	1	11
	1.1%	0.3%	0.3%	1.1%	0.3%	3.0%
2-3 year	9	12	7	7	17	52
	2.5%	3.3%	1.9%	1.9%	4.7%	14.3%
3-4 year	12	10	19	16	18	75
	3.3%	2.7%	5.2%	4.4%	4.5%	20.6%
4 -5 year	14	31	36	44	44	169
	3.8	8.5%	9.9%	12.0%	12.0%	46.4%
5 year or more.	3	6	18	14	16	57
	0.8%	1.6%	4.5%	3.8%	4.4%	15.7%
Total	42	60	81	85	96	364
	11.5%	16.5%	22.2%	23.4	26.4%	100.0%

Cross-tabulation (experience of employees by level of usage AI)

The results of the cross-tabulation for experience of employees by level of usage are presented in Table 6.31 and in Figure 6.10 below. Reveals that the majority of respondents about experience of who are used AI applications frequently 31.6%, while the minority are about experience of employees who not used at all just 7.2% of 26 respondents. The percentage of those respondents who use the AI applications extensively are: 0.3%for who has 1–2-year experience, 0.6% for employees who has the 2–3-year experience, 1.6% for 3–4-year experience, 5.2% for employees who 4 -5-year experience, 3.0% for employees who has 5 year or more experience. The total percentage of all industry respondents who use the AI applications extensively is 10.7%. The percentage of those respondents who use the AI applications frequently are: 0.0% for who has 1–2-year experience, 4.5% for employees who has the 2–3-year experience, 6.0% for 3–4-year experience, 14.7% for employees who 4 -5-year experience, 6.0% for employees who has 5 year or more experience. The total percentage of all industry respondents who use the AI applications frequently is 31.6%. The percentage of those respondents who use the AI applications quite often are: 0.6% for who has 1–2-year experience, 2.2% for employees who has the 2–3-year experience, 3.8% for 3–4-year experience, 10.7% for employees who 4 -5-year experience, 3.3% for employees who has 5 year or more experience. The total percentage of all industry respondents who use the AI applications quite often is 20.6%. The percentage of those respondents who use the AI applications rarely are: 1.9% for who has 1–2-year experience, 5.2% or employees who has the 2–3-year experience, 7.1% for 3–4-year experience, 12.9% for employees who 4 -5-year experience, 2.7% for employees who has 5 year or more experience. The total percentage of all industry respondents who use the AI applications rarely is 29.9%. The percentage of those respondents who do not use the AI applications are: 0.3% for who has 1–2-year experience, 1.4% or employees who has the 2–3-year experience, 1.9% for 3–4-year experience, 3.0% for employees who 4 -5-year experience, 0.6% for employees who has 5 year or more experience. The total percentage of all industry respondents who do not use the AI applications quite often is 7.2%.

Table 6.31: Cross-tabulation (experience of employees by usage)

Employment Experience	**Usage**					**Total**
	not used at all	used rarely	used quite often	used frequently	used extensively	
1-2 year	1	7	2	0	1	11

	0.3%	1.9%	0.6%	0	0.3%	3.0%
2-3 year	5	19	8	18	2	52
	1.4%	5.2%	2.2%	4.5%	0.6%	14.3%
3-4 year	7	26	14	22	6	75
	1.9%	7.1%	3.8%	6.0%	1.6%	20.6%
4 -5 year	11	47	39	53	19	169
	3.0%	12.9%	10.7%	14.7%	5.2%	46.4%
5 year or more.	2	10	12	22	11	57
	0.6%	2.7%	3.3%	6.0%	3.0%	15.7%
Total	26	109	75	115	39	364
	7.2%	29.9%	20.6%	31.6%	10.7%	100.0%

Cross-tabulation (experience of employees by Type of Application)

The results of the cross-tabulation for experience of employees by Application are presented in Table 6.32 below and reveals that the majority of respondents about experience of who are used AI applications from 1-2 application, while the minority are about experience of employees who not used AI applications. The percentage of those respondents who use the 5 and above AI applications are: 0.0% for who has 1–2-year experience, 0.8%% for employees who has the 2–3-year experience, 1.9% for 3–4-year experience, 4.7% for employees who 4 -5-year experience, 2.7% for employees who has 5 year or more experience. The total percentage of all respondents who use the AI applications the 5 and above types is 10.2%. The percentage of those respondents who use 3-4 AI applications are: 0.6% for who has 1–2-year experience, 2.2% for employees who has the 2–3-year experience, 3.5% for 3–4-year experience, 7.7% for employees who 4 -5-year experience, 1.7% for employees who has 5 year or more experience. The total percentage of all respondents who use the AI applications 2-3 types is 15.6%. The percentage of those respondents who use 2-3 AI applications are: 0.8% for who has 1–2-year experience, 5.2% for employees who has the 2–3-year experience, 5.5% for 3–4-year experience, 12.4% for employees who 4 -5-year experience, 4.1% for employees who has 5 year or more experience. The total percentage of all respondents who use the AI applications 2-3 types is 28.0%. The percentage of those respondents who use 1-2 AI applications are: 1.1% for who has 1–2-year experience, 4.7% for employees who has the 2–3-year experience, 8.5% for 3–4-year experience, 20.6% for employees who 4 -5-year experience, 6.6% for employees who has 5 year or more experience. The total percentage of all respondents who use the AI applications 1-2 types is 41.5%. The percentage of those respondents who do not use any AI applications are: 0.6% for who has 1–2-year experience, 1.4% for employees who has the 2–3-year experience, 1.1% for 3–4-year experience, 1.1% for employees who 4 -5-year experience, 0.6% for employees who has 5 year or more experience. The total percentage of all respondents who use the AI applications 1-2 types is 4.7%.

Table 6.32: Cross-tabulation (experience of employees by application)

Employment Experience	Application					Total
	none	1-2	2-3	3-4	5 and above	
1-2 year	2	4	3	2	0	11
	0.6%	1.1%	0.8%	0.6%	0	3.0%
2-3 year	5	17	19	8	3	52
	1.4%	4.7%	5.2%	2.2%	0.8%	14.3%
3-4 year	4	31	20	13	7	75
	1.1%	8.5%	5.5%	3.5%	1.9%	20.6%
4 -5 year	4	75	45	28	17	169
	1.1%	20.6%	12.4%	7.7%	4.7%	46.4%
5 year or more.	2	24	15	6	10	57
	0.6%	6.6%	4.1%	1.7%	2.7%	15.7%
Total	17	151	102	57	37	364
	4.7%	41.5%	28.0%	15.6%	10.2%	100.0%

Cross-tabulation (experience of employees by Features)

The results of the cross-tabulation for experience of employees by Features are presented in Table 6.33 below and reveals that the majority of respondents about experience of who are used AI applications rarely, while the minority are about experience of employees who use extensively AI applications. The percentage of those respondents who use AI applications extensively are: 0.0% for who has 1–2-year experience, 0.6% for employees who has the 2–3-year experience, 1.7% for 3–4-year experience, 4.1% for employees who 4 -5-year experience, 1.9% for employees who has 5 year or more experience. The total percentage of all respondents who use the AI applications extensively is 8.3%. The percentage of those respondents who use AI applications frequently are: 0.6% for who has 1–2-year experience, 3.3% for employees who has the 2–3-year experience, 2.7% for 3–4-year experience, 7.7% for employees who 4 -5-year experience, 4.4% for employees who has 5 year or more experience. The total percentage of all respondents who use the AI applications frequently is 18.7%. The percentage of those respondents who use AI applications quite often are: 0.0% for who has 1–2-year experience, 3.8% for employees who has the 2–3-year experience, 6.0% for 3–4-year experience, 13.7% for employees who 4 -5-year experience, 2.7% for employees who has 5 year or more experience. The total percentage of all respondents who use the AI applications quite often is 26.4%. The percentage of those respondents who do not use AI applications are: 0.3% for who has 1–2-year experience, 2.5% for employees who has the 2–3-year experience, 2.2% for 3–4-year experience, 5.2% for employees who 4 -5-year experience, 1.9% for employees who has 5 year or more experience. The total percentage of all respondents who do not use the AI applications is 12.1%.

Table 6.33: Cross-tabulation (experience of employees by Features)

Employment Experience	**Features**					**Total**
	not used at all	used rarely	used quite often	used frequently	used extensivel y	
1-2 year	1	8	0	2	0	11
	0.3%	2.2%	0	0.6%	0	3.0%
2-3 year	9	15	14	12	2	52
	2.5%	4.2%	3.8%	3.3%	0.6%	14.3%
3-4 year	8	29	22	10	6	75
	2.2%	8.0%	6.0%	2.7%	1.7%	20.6%
4 -5 year	19	57	50	28	15	169
	5.2%	5.7%	13.7%	7.7%	4.1%	46.4%
5 year or more.	7	17	10	16	7	57
	1.9%	4.7%	2.7%	4.4%	1.9%	15.7%
Total	44	126	96	68	30	364
	12.1%	34.6%	26.4%	18.7%	8.3%	100.0%

Cross-tabulation for Industry classification

Cross-tabulation (Industry classification by time)

The results of the cross-tabulation for Industry classification by time are presented in Table 6.34 below and reveals that the majority of respondents are in the information, communication & technology Industry, while the minority are in Tourism Industry. The percentage of those respondents who use the AI applications more than 4 hours are: 2.5% for the Construction and building material industry, 0.8% for the Automotive-related repair maintenance & traded, 2.5% for the Wholesale and retail trade (non-automotive), 2.5% for the Finance and insurance, 1.1%

for the Food & beverage. 0.8% for the agriculture industry, 7.4% for the Information, communication & technology, 0.5% for the Tourism, 0.8% for the Real estate and 5.7% for the other services industry. The total percentage of all industry respondents who use the AI applications more than 4 hours per week is 24.7%. The percentage of those respondents who use the AI applications 3-4 hours are: 1.4%for the construction and building material industry, 1.4%for the Automotive-related repair maintenance & traded, 1.4% for the Wholesale and retail trade (non-automotive), 2.5%bfor the Finance and insurance, 1.9% for the Food & beverage. 0.8% for the agriculture industry, 4.4% for the Information, communication & technology, 0.3% for the Tourism, 0.8% for the Real estate and 4.4% for the other services industry. The total percentage of all industry respondents who use the AI applications 3-4 hours per week is 19.2%. The percentage of those respondents who use the AI applications 2-3 hours are: 1.1%for the construction and building material industry, 0.6% for the Automotive-related repair maintenance & traded, 1.7% for the Wholesale and retail trade (non-automotive), 1.4% for the Finance and insurance, 1.7% for the Food & beverage. 0.8% for the agriculture industry, 6.0% for the Information, communication & technology, 0.3% for the Tourism, 0.0% for the Real estate and 6.6% for the other services industry. The total percentage of all industry respondents who use the AI applications 2-3 hours per week is 20.1%. The percentage of those respondents who use the AI applications 1-2 hours are: 1.9% for the construction and building material industry, 0.3% for the Automotive-related repair maintenance & traded, 2.7% for the Wholesale and retail trade (non-automotive), 1.7% for the Finance and insurance, 1.4% for the Food & beverage. 0.6% for the agriculture industry, 5.2% for the Information, communication & technology, 0.0% for the Tourism, 0.8% for the Real estate and 4.7% for the other services industry. The total percentage of all industry respondents who use the AI applications 1-2 hours per week is 19.2%. The percentage of those respondents who use the AI applications for less than 1 hour are: 1.1% for the construction and building material industry, 1.3% for the Automotive-related repair maintenance & traded, 0.3% for the Wholesale and retail trade (non-automotive), 2.2% for the Finance and insurance, 4.1% for the Food & beverage. 0.6%for the agriculture industry, 5.0% for the Information, communication & technology, 0.3% for the Tourism, 0.6% for the Real estate and 2.7% for the other services industry. The total percentage of all industry respondents who use the AI applications for less than 1 hour per week is 16.8%.

Table 6.34: Cross-tabulation (Industry classification by time)

Industry classification	Time					Total
	Less than 1 hour	1-2 hours	2-3 hours	3-4 hours	(More than 4 hours	
Construction and building material	4	7	4	5	9	29
	1.1%	1.9%	1.1%	1.4%	2.5%	8.0%
Automotive-related repair maintenance & traded	1	1	2	5	3	12
	0.3%	0.3%	0.6%	1.4%	0.8%	3.3%
Wholesale and retail trade (non-automotive	8	10	6	5	9	38
	2.2%	2.7%	1.7%	1.4%	2.5%	10.4%
Finance and insurance	15	6	5	9	9	44
	4.1	1.7%	1.4%	2.5%	2.5%	12.2%
Food & beverage	2	5	6	7	4	24
	0.6%	1.4%	1.7%	1.9%	1.1%	6.6%
Agriculture	0	2	3	3	3	11
	0	0.6%	0.8%	0.8%	0.8%	3.0%
Information, communication & technology	18	19	22	16	27	102
	5.0%	5.2%	6.0%	4.4%	7.4%	28.0%
Tourism	1	0	1	1	2	5
	0.3%	0	0.3%	0.3%	0.5%	1.4%
Real estate	2	3	0	3	3	11
	0.6%	0.8%	0	0.8%	0.8%	3.0%
Other services	10	17	24	16	21	88
	2.7%	4.7%	6.6%	4.4%	5.7%	24.1%
Total	61	70	73	70	90	364
	16.8%	19.2%	20.1%	19.2%	24.7%	100%

Cross-tabulation (Industry classification by frequency)

The results of the cross-tabulation for Industry classification by frequency are presented in Table 6.35 below. The percentage of those respondents who use the AI applications several times a day are: 2.7% for the Construction and building material industry, 0.3% for the Automotive-related repair maintenance & traded, 2.2% for the Wholesale and retail trade (non-automotive), 3.0% for the Finance and insurance, 1.4% for the Food & beverage. 0.6%for the agriculture industry, 9.0% for the Information, communication & technology, 0.3%for the Tourism, 0.3% for the Real estate and 6.6% for the other services industry. The total percentage of all industry respondents who use the AI applications several times a day per week is 26.3%. The percentage of those respondents who use the AI applications once a day are: 1.4% for the construction and building material industry, 1.4% for the Automotive-related repair maintenance & traded, 3.8% for the Wholesale and retail trade (non-automotive), 1.7% for the Finance and insurance, 1.9% for the Food & beverage. 1.7% for the agriculture industry, 3.6% for the Information, communication & technology, 0.0% for the Tourism, 1.7% for the Real estate and 6.3% for the other services industry. The total percentage of all industry respondents who use the AI applications a few times a month is 23.4%. The percentage of those respondents who use the AI applications a few times a month are: 2.2% for the construction and building material industry, 0.8% for the Automotive-related repair maintenance & traded, 1.7% for the Wholesale and retail trade (non-automotive), 2.7% for the Finance and insurance, 1.1% for the Food & beverage. 0.6%for the agriculture industry, 6.7% for the Information, communication & technology, 0.6% for the Tourism, 0.3% for the Real estate and 5.5% for the other services industry. The total percentage of all industry respondents who use the AI applications a few times a month is 22.3%. The percentage of those respondents who use the AI applications once a month are: 1.1% for the construction and building material industry, 0.6% for the Automotive-related repair maintenance & traded, 1.4% for the Wholesale and retail trade (non-automotive), 2.2% for the Finance and insurance, 1.4% for the Food & beverage. 0.3% for the agriculture industry, 4.7% for the Information, communication & technology, 0.3% for the Tourism, 0.6% for the Real estate and 4.1% for the other services industry. The total percentage of all industry respondents who use the AI applications once a month is 16.5%. The percentage of those respondents who use the AI applications for less than once a month are: 0.6% for the construction and building material industry, 0.3% for the Automotive-related repair maintenance & traded, 1.4% for the Wholesale and retail trade (non-automotive), 2.5% for the Finance and insurance, 0.8% for the Food & beverage. 0.0% for the agriculture industry, 3.8% for the Information, communication & technology, 0.3% for the Tourism, 0.3% for the real estate and 1.7% for the other services industry. The total percentage of all industry respondents who use the AI applications for less than once a month is 11.5%. The findings show that 26.3% of the respondents from all industries used AI several times a day, while 11.5% from all industries the lowset percentage used AI less than once a month.

Table 6.35: Cross-tabulation (Industry classification frequency)

Industry classification	**frequency**					**Total**
	less than once a month	once a month	a few times a month	once a day	several times a day	

Construction and building material	2	4	8	5	10	29
	0.6%	1.1%	2.2%	1.4%	2.7%	8.0%
Automotive-related repair maintenance & traded	1	2	3	5	1	12
	0.3%	0.6%	0.8%	1.4%	0.3%	3.3%
Wholesale and retail trade (non-automotive	5	5	6	14	8	38
	1.4%	1.4%	1.7%	3.8%	2.2%	10.4%
Finance and insurance	9	8	10	6	11	44
	2.5%	2.2%	2.8%	1.7%	3.0%	12.2%
Food & beverage	3	5	4	7	5	24
	0.8%	1.4%	1.1%	1.9%	1.4%	6.6%
Agriculture	0	1	2	6	2	11
	0	0.3%	0.6%	1.7%	0.6%	3.0%
Information, communication & technology	14	17	25	13	33	102
	3.8%	4.7%	6.7%	3.6%	9.0%	28.0%
Tourism	1	1	2	0	1	5
	0.3%	0.3%	0.6%	0	0.3%	1.4%
Real estate	1	2	1	6	1	11
	0.3%	0.6%	0.3%	1.7%	0.3%	3.0%
Other services	6	15	20	23	24	88
	1.7%	4.1	5.5%	6.3%	6.6%	24.1%
Total	42	60	81	85	96	364
	11.5%	16.5%	22.3%	23.4%	26.3%	100%

Cross-tabulation (Industry classification by usage)

The results of the cross-tabulation for industry classification by Level of usage are presented in Table 6.36 and in Figure 6.11 below. The percentage of those respondents who use the AI applications Used extensively are: 1.1% for the Construction and building material industry, 0.3% for the Automotive-related repair maintenance & traded, 0.8% for the Wholesale and retail trade (non-automotive), 0.6% for the Finance and insurance, 0.0% for the Food & beverage. 0.3%f or the agriculture industry, 4.7% for the Information, communication & technology, 0.00% for the Tourism, 0.00% for the Real estate and 3.0% for the other services industry. The total percentage of all industry respondents who use the AI applications extensively is 10.7%. The percentage of those respondents who use the AI applications frequently are: 1.4% for the construction and building material industry, 1.4% for the Automotive-related repair maintenance & traded, 2.7% for the Wholesale and retail trade (non-automotive), 3.3% for the Finance and insurance, 2.2% for the Food & beverage. 0.8% for the agriculture industry, 9.3% for the Information, communication & technology, 0.6% for the

Tourism, 9.3% for the real estate and 6.3% for the other services industry. The total percentage of all industry respondents who use the AI applications a few times a month is 31.6%. The percentage of those respondents who use the AI applications quite often a month are: 1.1% for the construction and building material industry, 1.1% for the Automotive-related repair maintenance & traded, 1.9% for the Wholesale and retail trade (non-automotive), 3.0% for the Finance and insurance, 1.7% for the Food & beverage. 0.6% for the agriculture industry, 5.8% for the Information, communication & technology, 0.3% for the Tourism 0.6% for the Real estate and 4.7% for the other services industry. The total percentage of all industry respondents who use the AI applications quite often a month is 20.60%. The percentage of those respondents who use the AI applications rarely are: 3.3% for the construction and building material industry, 0.5% for the Automotive-related repair maintenance & traded, 4.7% for the Wholesale and retail trade (non-automotive), 17% for the Finance and insurance, 2.2% for the Food & beverage. 1.4% for the agriculture industry, 5.8% for the Information, communication & technology, 0.0% for the Tourism, 1.9% for the Real estate and 5.8% for the other services industry. The total percentage of all industry respondents who use the AI applications rarely is 30%. The percentage of those respondents who do not use the AI applications at all are: 1.1% for the construction and building material industry, 0.0% for the Automotive-related repair maintenance & traded, 0.3% for the Wholesale and retail trade (non-automotive), 0.8% for the Finance and insurance, 0.6% for the Food & beverage. 0.0% for the agriculture industry, 2.5% for the Information, communication & technology, 0.6% for the Tourism, 0.0% for the real estate and 1.4% for the other services industry. The total percentage of all industry respondents who use the AI applications for less than once a month is 7.1%. The findings show that 31.6% of the respondents from all industries used frequently day, while 7.1% from all industries the lowset percentage does not use the AI applications at all.

Table 6.36: Cross-tabulation (Industry classification by usage)

Industry classification	**Usage**					**Total**
	Not used at all	Used rarely	Used quite often	Used frequently	Used extensively	
Construction and building material	4	12	4	5	4	29
	1.1%	3.3%	1.1%	1.4%	1.1%	8.0%

Automotive-related repair maintenance & traded	0	2	4	5	1	12
	0	0.5%	1.1%	1.4%	0.3%	3.3%
Wholesale and retail trade (non-automotive	1	17	7	10	3	38
	0.3%	4.7%	1.9%	2.7%	0.8%	10.4%
Finance and insurance	3	16	11	12	2	44
	0.8%	17%	3.0%	3.3%	0.6%	12.2%
Food & beverage	2	8	6	8	0	24
	0.6%	2.2%	1.7%	2.2%	0	6.6%
Agriculture	0	5	2	3	1	11
	0	1.4%	0.6%	0.8%	0.3%	3.0%
Information, communication & technology	9	21	21	34		102
	2.5%	5.8%	5.8%	9.3%	17	28.0%
Tourism	2	0	1	2	4.7%	5
	0.6%	0	0.3%	0.6%	0	1.4%
Real estate	0	7	2	2	0	11
	0	1.9%	0.6%	0.6%	0	3.0%
Other services	5	21	17	34	0	88
	1.4%	5.8%	4.7%	9.3%	11	24.1%
Total	26	109	75	115	3.0%	364
	7.1%	30%	20.60%	31.6%	39	100%

Cross-tabulation (Industry classification by application)

The results of the cross-tabulation for Industry classification by application are presented in Table 6. 37 below. The percentage of those respondents who use 5 AI applications and above: 1.4% for the Construction and building material industry, 0.5% for the Automotive-related repair maintenance & traded, 1.1% for the Wholesale and retail trade (non-automotive), 0.5% for the Finance and insurance, 0.3% for the Food & beverage. 0.3%f or the agriculture industry, 3.8% for the Information, communication & technology, 0.00% for the Tourism, 0.5% for the Real estate and 1.7% for the other services industry. The total percentage of all industry respondents who use 5 AI applications and above is 10.2%. The percentage of those respondents who use 3–4 AI applications are: 1.4% for the construction and building material industry, 0.3% for the Automotive-related repair maintenance & traded, 1.1% for the Wholesale and retail trade (non-automotive), 1.7% for the Finance and insurance, 1.4% for the Food & beverage. 0.3% for the agriculture industry, 4.7% for the Information, communication & technology, 0.5% for the Tourism, 0.8% for the real estate and 3.6%for the other services industry. The total percentage of all industry respondents who use the AI applications a few times a month is 15.6%. The percentage of those respondents who use 2–3 AI applications are: 0.8% for the construction and building material industry, 1.1% for the Automotive-related repair maintenance & traded, 1.7% for the Wholesale and retail trade (non-automotive), 3.6% for the Finance and insurance, 2.5% for the Food & beverage. 1.1% for the agriculture industry, 8.0% for the Information, communication & technology, 0.3% for the Tourism 0.5% for the Real estate and 8.5% for the other services industry. The total percentage of all industry respondents who use 2–3 AI applications is 28%. The percentage of those respondents who use 1–2 AI applications are: 2.8% for the construction and building material industry, 1.4% for the Automotive-related repair maintenance & traded, 6.3% for the Wholesale and retail trade (non-automotive), 5.5% for the Finance and insurance, 2.2% for the Food & beverage. 1.4% for the agriculture industry, 10.4% for the Information, communication & technology, 0.3% for the Tourism, 1.1% for the Real estate and 9.1% for the other services industry. The total percentage of all industry respondents who use 1–2 AI applications is 41.5%. The percentage of those respondents who do not use AI applications are: 0.5% for the construction and building material industry, 0.0% for the Automotive-related repair maintenance & traded, 0.3% for the Wholesale and retail trade (non-automotive), 0.8% for the Finance and insurance, 0.3% for the Food & beverage. 0.0% for the agriculture industry, 1.1% for the Information, communication & technology, 0.3% for the Tourism, 0.0% for the real estate and 1.4% for the other services industry. The total percentage of all industry respondents who do not use AI applications is 4.7%.

Table 6.37: Cross-tabulation (Industry classification by application)

Industry classification	**Application**					**Total**
	None	1–2	2–3	3–4	5 & above	
Construction and building material	2	14	3	5	5	29
	0.5%	2.8%	0.8%	1.4%	1.4%	8.0%
Automotive-related repair maintenance & traded	0	5	4	1	2	12
	0	1.4%	1.1%	0.3%	0.5%	3.3%
Wholesale and retail trade (non-automotive	1	23	6	4	4	38
	0.3%	6.3%	1.7%	1.1%	1.1%	10.4%
Finance and insurance	3	20	13	6	2	44
	0.8%	5.5%	3.6%	1.7%	0.5%	12.2%
Food & beverage	1	8	9	5	1	24
	0.3%	2.2%	2.5%	1.4%	0.3%	6.6%
Agriculture	0	5	4	1	1	11

	0	1.4%	1.1%	0.3%	0.3%	3.0%
Information, communication & technology	4	38	29	17	14	102
	1.1%	10.4%	8.0%	4.7%	3.8%	28.0%
Tourism	1	1	1	2	0	5
	0.3%	0.3%	0.3%	0.5%	0	1.4%
Real estate	0	4	2	3	2	11
	0	1.1%	0.5%	0.8%	0.5%	3.0%
Other services	5	33	31	13	6	88
	1.4%	9.1%	8.5%	3.6%	1.7%	24.1%
Total	17	151	102	57	37	364
	4.7%	41.5%	28%	15.6%	10.2%	100%

Cross-tabulation (Industry classification by features)

The results of the cross-tabulation for Industry classification by application are presented in Table 6. 38. The percentage of those 2 respondents who use extensively: 0.5% for the Construction and building material industry, 0.8% for the Automotive-related repair maintenance & traded, 0.8% for the Wholesale and retail trade (non-automotive), 1.1% for the Finance and insurance, 0.5% for the Food & beverage. 0.0%f or the agriculture industry, 3.0% for the Information, communication & technology, 0.00% for the Tourism, 0.3% for the Real estate and 1.7% for the other services industry. The total percentage of all industry respondents who use extensively is 8.3%. The percentage of those 4 respondents who use frequently: 1.1% for the Construction and building material industry, 0.8% for the Automotive-related repair maintenance & traded, 2.2% for the Wholesale and retail trade (non-automotive), 1.9% for the Finance and insurance, 0.5% for the Food & beverage. 0.8%f or the agriculture industry, 4.9% for the Information, communication & technology, 0.3% for the Tourism, 0.5% for the Real estate and 5.5% for the other services industry. The total percentage of all industry respondents who use frequently is 18.7%. The percentage of those 8 respondents who use quite often: 2.2% for the construction and building material industry, 0.3% for the Automotive-related repair maintenance & traded, 1.4% for the Wholesale and retail trade (non-automotive), 3.3% for the Finance and insurance, 1.7% for the Food & beverage. 0.3%f or the agriculture industry, 8.8% for the Information, communication & technology, 0.3% for the Tourism, 0.8% for the Real estate and 7.4% for the other services industry. The total percentage of all industry 96 respondents who use quite often is 26.3%. The percentage of those 8 respondents who use rarely: 2.2% for the construction and building material industry, 0.8% for the Automotive-related repair maintenance & traded, 4.7% for the Wholesale and retail trade (non-automotive), 4.4% for the Finance and insurance, 2.7% for the Food & beverage. 1.7%f or the agriculture industry, 9.1% for the Information, communication & technology, 0.5% for the Tourism, 1.1% for the Real estate and 7.4% for the other services industry. The total percentage of all industry 126 respondents who use rarely is 34.%. The percentage of those 7 respondents who did not used AI application at all: 1.9% for the construction and building material industry, 0.5% for the Automotive-related repair maintenance & traded, 1.4% for the Wholesale and retail trade (non-automotive), 1.1% for the Finance and insurance, 0.3% for the Food & beverage. 2.2%f or the agriculture industry, 0.3% for the Information, communication & technology, 0.5% for the Tourism, 1.1% for the Real estate and 2.7% for the other services industry. The total percentage of all industry 44 respondents who did not used AI application at all is 12.1%.

Table 6.38: Cross-tabulation (Industry classification by features)

Industry classification	**Features**					**Total**
	Not used at all	Used rarely	Used quite often	Used frequently	Used extensively	
Construction and building material	7	8	8	4	2	29
	1.9%	2.2%	2.2%	1.1%	0.5%	8.0%
Automotive-related repair maintenance & traded	2	3	1	3	3	12
	0.5%	0.8%	0.3%	0.8%	0.8%	3.3%
Wholesale and retail trade (non-automotive	5	17	5	8	3	38
	1.4%	4.7%	1.4%	2.2%	0.8%	10.4%
Finance and insurance	5	16	12	7	4	44
	1.4%	4.4%	3.3%	1.9%	1.1%	12.2%
Food & beverage	4	10	6	2	2	24
	1.1%	2.7%	1.7%	0.5%	0.5%	6.6%
Agriculture	1	6	1	3	0	11
	0.3%	1.7%	0.3%	0.8%	0	3.0%
Information, communication & technology	8	33	32	18	11	102
	2.2%	9.1%	8.8%	4.9%	3.0%	28.0%
Tourism	1	2	1	1	0	5
	0.3%	0.5%	0.3%	0.3%	0	1.4%
Real estate	1	4	3	2	1	11
	0.3%	1.1%	0.8%	0.5%	0.3%	3.0%
Other services	10	27	27	20	4	88
	2.7%	7.4%	7.4%	5.5%	1.1%	24.1%
Total	44	126	96	68	30	364
	12.1%	34.6%	26.3%	18.7%	8.3%	100%

Cross-tabulation for number of employees

Cross-tabulation (Number of employees by time)

The results of the cross-tabulation for number of employees by time are presented in Table 6.39 below. The results indicate that 54 the respondents from SMEs who had number of employees from 20-99 employees used AI applications more than 5 hours as the highest percentage it is 14.8%, compared with 0.8% of 3 respondents from SMEs who had non workers and 3 respondents' employees from 1-4. In the meantime, 7 the respondents from SMEs who had 5-19 employees 1.9%. and 23 the respondents from SMEs who had 99- 250 employees is 6.3%. Results also indicate that 24.7% of the 90 respondents from all number of employees categories used AI applications more than 5 hours. The results indicate that 40 the respondents from SMEs who had number of employees from 20-99 employees used AI applications 3-4 hours with percentage it is 11.0% compared with 0.0% of respondents from SMEs who had non workers and 4 respondents' employees from 1-4. With percentage is 1.1%. In the meantime, 10 the respondents from SMEs who had 5-19 employees 2.7% and 16 the respondents from SMEs who had 99- 250 employees is 4.4%. Results also indicate that 19.2% of the 70 respondents from all number of employees categories used AI applications 3-4 hours. The results indicate that 43 the respondents from SMEs who had number of employees from 20-99 employees used AI applications 2-3 hours with percentage it is 11.8% compared with 0.5% of 2 respondents from both SMEs for who had non workers employees from 1-4. In the meantime, 9 the respondents from SMEs who had 5-19 employees 2.5% and 17 the respondents from SMEs who had 99- 250 employees is 4.7%. Results also indicate that 20.1% of the 73 respondents from all number of employees categories used AI applications 2-3 hours. The results indicate that 41 the respondents from SMEs who had number of employees from 20-99 employees used AI applications 1-2 hours with percentage it is 11.3% compared with 0.0% of the respondents from SMEs for who had nonemployees. Also, 9 the respondents from SMEs who had number of employees from 1-4 with percentage 2.5%. In the meantime, 11 the respondents from SMEs who had 5-19 employees 3.0% and 9 the respondents from SMEs who had 99- 250 employees is 2.5%. Results also indicate that 19.2% of the 70 respondents from all number of employees categories used AI applications 1-2 hours. The results indicate that 29 the respondents from SMEs who had number of employees from 20-99 employees used AI applications for less than 1 hour with percentage it is 8.0% compared with 1.4% of 5the respondents from SMEs for who had nonemployees. Also, 9 the respondents from SMEs who had number of employees from 1-4 with percentage 2.5%. In the meantime, 12 the respondents from SMEs who had 5-19 employees 3.3% and 6 the respondents from SMEs who had 99- 250 employees is 1.7%. Results also indicate that 16.8% of the 61 respondents from all number of employees categories used AI applications 1-2 hours.

Table 6.39: Cross-tabulation (Number of employees by time)

Number of Employees	Time					Total
	Less than 1 hour	1-2 hours	2-3 hours	3-4 hours	More than 5 hours	
Non	5	0	2	0	3	10
	1.4%	0	0.5%	0	0.8%	2.7%
1-4	9	9	2	4	3	27
	2.5%	2.5%	0.5%	1.1%	0.8%	7.4%
5-19	12	11	9	10	7	49
	3.3%	3.0%	2.5%	2.7%	1.9%	13.5%
20-99	29	41	43	40	54	207
	8.0%	11.3%	11.8%	11.0%	14.8%	56.9%
99- 250	6	9	17	16	23	71
	1.7%	2.5%	4.7%	4.4%	6.3%	19.5%
Total	61	70	73	70	90	364
	16.8%	19.2%	20.1%	19.2%	24.7%	100%

Cross-tabulation (Number of employees by frequently

The results of the cross-tabulation for number of employees by frequently are presented in Table 6.40 below. The results indicate that 55 the respondents from SMEs who had number of employees from 20-99 employees used AI applications several times a day as the highest percentage it is 15.2%, compared with 0.5% of 2 respondents from SMEs who had non workers and 5 respondents' employees from 1-4 with percentage it is 1.4%. In the meantime, 10the respondents from SMEs who had 5-19 employees 2.7%. and 24 the respondents from SMEs who had 99- 250 employees is 6.6%. Results also indicate that 26.4% of the 96 respondents from all number of employees categories used AI applications several times a day. The results indicate that 53 the respondents from SMEs who had number of employees from 20-99 employees used AI applications once a day with percentage it is 14.6% compared with 0.0% of respondents from SMEs who had non workers and 4 respondents' employees from 1-4. With percentage is 1.1%. In the meantime, 11 the respondents from SMEs who had 5-19 employees 3.0% and 17 the respondents from SMEs who had 99- 250 employees is 4.7%. Results also indicate that 23.3% of the 85 respondents from all number of employees categories used AI applications once a day. The results indicate that 52 the respondents from SMEs who had number of employees from 20-99 employees used AI applications a few times a month with percentage it is 14.3% compared with 0.8% of 3 respondents from both SMEs for who had non workers. with 0.8% of 3 respondents from SMEs employees from 1-4 as well. In the meantime, 10 the respondents from SMEs who had 5-19 employees 2.7% and 13 the respondents from SMEs who had 99- 250 employees is 3.6%. Results also indicate that 22.3% of the 81 respondents from all number of employees categories used a few times a month. The results indicate that 30 the respondents from SMEs who had number of employees from 20-99 employees used AI applications once a month with percentage it is 8.3% compared with 0.3% of one respondent from SMEs for who had nonemployees. Also, 6 the respondents from SMEs who had number of employees from 1-4 with percentage 1.7%. In the meantime, 10 the respondents from SMEs who had 5-19 employees 2.7% and 13 the respondents from SMEs who had 99- 250 employees is 36%. Results also indicate that 16.5% of the 60 respondents from all number of employees categories used AI applications once a month. The results indicate that 17 the respondents from SMEs who had number of employees from 20-99 employees used AI applications for less than once a month with percentage it is 4.7% compared with 1.1% of 4 the respondents from SMEs for who had nonemployees. Also, 9 the respondents from SMEs who had number of employees from 1-4 with percentage 2.5%. In the meantime, 8.0% the respondents from SMEs who had 5-19 employees 2.2% and 4 the respondents from SMEs who had 99- 250 employees is 1.1%. Results also indicate that 11.5% of the 42 respondents from all number of employees categories used AI applications for less than once a month.

Table 6.40: Cross-tabulation (Number of employees by frequently)

Number of Employees	**Frequently**					**Total**
	less than once a month	once a month	a few times a month	once a day	several times a day	
Non	4	1	3	0	2	10
	1.1%	0.3%	0.8%	0	0.5%	2.7%
4	9	6	3	4	5	27
	2.5%	1.7%	0.8%	1.1%	1.4%	7.4%
5-19	8	10	10	11	10	49
	2.2%	2.7%	2.7%	3.0%	2.7%	13.5%
20-99.	17	30	52	53	55	207

	4.7%	8.3%	14.3%	14.6%	15.2%	56.9%
99-250	4	13	13	17	24	71
	1.1%	3.6%	3.6%	4.7%	6.6%	19.5%
Total	42	60	81	85	96	364
	11.5%	16.5%	22.3%	23.3%	26.4%	100%

Cross-tabulation (Number of employees by usage)

The results of the cross-tabulation for number of employees by level of usage are presented in Table 6.41 and in Figure 6.12 below. The results indicate that 28 the respondents from SMEs who had number of employees from 20-99 employees used AI applications used frequently as the highest percentage it is 19.0%, compared with 0.5% of 2 respondents from SMEs who had non workers and 7 respondents' employees from 1-4 with percentage it is 1.9%. In the meantime, 9 the respondents from SMEs who had 5-19 employees 2.5%. and 28 the respondents from SMEs who had 99- 250 employees is 7.7%. Results also indicate that 31.6% of the 115 respondents from all number of employees categories used AI applications used frequently. The results indicate that 46 the respondents from SMEs who had number of employees from 20-99 employees used AI applications used quite often with percentage it is 12.6% compared with 0.8% of 3 respondents from SMEs who had non workers and 2 respondents' employees from 1-4. with percentage is 0.5%. In the meantime, 13 the respondents from SMEs who had 5-19 employees 3.6% and 11 the respondents from SMEs who had 99- 250 employees is 3.0%. Results also indicate that 20.6% of the 75 respondents from all number of employees categories used AI applications used quite often. The results indicate that 59 the respondents from SMEs who had number of employees from 20-99 employees used AI applications used rarely with percentage it is 15.4% compared with 0.8% of 3 respondents from both SMEs for who had non workers. with 4.1% of 15 respondents from SMEs employees from 1-4 as well. In the meantime, 16 the respondents from SMEs who had 5-19 employees 4.4% and 16 the respondents from SMEs who had 99- 250 employees is 4.4%. Results also indicate that 29.9% of the 109 respondents from all number of employees categories used rarely. The results indicate that 24 the respondents from SMEs who had number of employees from 20-99 employees used AI applications used extensively with percentage it is 6.6% compared with 0.0% of respondent from SMEs for who had nonemployees. Also, one respondent from SMEs who had number of employees from 1-4 with percentage 0.3%. In the meantime, 5 the respondents from SMEs who had 5-19 employees 1.4% and 9 the respondents from SMEs who had 99- 250 employees is 2.5%. Results also indicate that 10.7% of the 39 respondents from all number of employees categories used AI applications used extensively. The results indicate that 9 the respondents from SMEs who had number of employees from 20-99 employees used AI applications not used at all with percentage it is 2.5% compared with. 0.5% of 2 the respondents from SMEs for who had nonemployees. Also, 2 the respondents from SMEs who had number of employees from 1-4 with percentage 0.5%. In the meantime, 6 respondents from SMEs who had 5-19 employees 1.7% and 7 the respondents from SMEs who had 99- 250 employees is 1.9%. Results also indicate that 11.5% of the 42 respondents from all number of employees categories used AI applications not used at all.

Table 6.41: Cross-tabulation (Number of employees by usage)

Number of Employees	**Usage**					**Total**
	not used at all	used rarely	used quite often	used frequently	used extensively	
Non	2	3	3	2	0	10
	0.5%	0.8%	0.8%	0.5%	0	2.7%
1-4	2	15	2	7	1	27
	0.5%	4.1%	0.5%	1.9%	0.3%	7.4%
5-19	6	16	13	9	5	49
	1.7%	4.4%	3.6%	2.5%	1.4%	13.5%
20-99	9	59	46	69	24	207
	2.5%	15.4%	12.6%	19%	6.6%	56.9%
99-250	7	16	11	28	9	71
	1.9%	4.4%	3.0%	7.7%	2.5%	19.5%
Total	26	109	75	115	39	364
	7.2%	29.9%	20.6%	31.6%	10.7%	100%

Cross-tabulation (Number of employees by application)

The results of the cross-tabulation for number of employees by type of application are presented in Table 6.42 below. The results indicate that 81 the respondents from SMEs who had number of employees from 20-99 employees used AI applications used (1-2) with percentage it is 22.3%, compared with 1.9% of 7 respondents from SMEs who had non workers and 11 respondents' employees from 1-4. with percentage is 3.0%. In the meantime, 20 the respondents from SMEs who had 5-19 employees 5.5% and 32 the respondents from SMEs who had 99- 250 employees is 8.8%. Results also indicate that 41.5% of the 151 respondents' highset percentage from all number of employees categories used AI applications used (1-2). The results indicate that 61 the respondents from SMEs who had number of employees from 20-99 employees used AI applications used (2-3) as the highest percentage it is 16.8%, compared with 0.5% of 2 respondents from SMEs who had non workers and 7 respondents' employees from 1-4 with percentage it is 1.9%. In the meantime16 the respondents from SMEs who had 5-19 employees 4.4%. and 16 the respondents from SMEs who had 99- 250 employees is 4.4%. Results also indicate that 28.0% of the 102 respondents from all number of employees categories used AI applications used (2-3). The results indicate that 34 the respondents from SMEs who had number of employees from 20-99 employees used AI applications used (3-4) with percentage it is 9.3%, compared with 0.0% of respondents from SMEs for who had non workers. with 0.5% of 2 respondents from SMEs employees from 1-4 as well. In the meantime, 5 the respondents from SMEs who had 5-19 employees 1.4% and 16 the respondents from SMEs who had 99- 250 employees is 4.4%. Results also indicate that 15.7% of the 57 respondents from all number of employees categories used (3-4). The results indicate that 24 the respondents from SMEs who had number of employees from 20-99 employees used AI applications used 5 AI applications and above with percentage it is 6.6% compared with 0.0% of respondent from SMEs for who had nonemployees. Also, 2 respondents from SMEs who had number of employees from 1-4 with percentage 0.5%. In the meantime, 5 the respondents from SMEs who had 5-19 employees 1.4% and 9 the respondents from SMEs who had 99- 250 employees is 2.5%. Results also indicate that 10.17% of the 37 respondents from all number of employees categories used 5 AI applications and above. The results indicate that 7 the respondents from SMEs who had number of employees from 20-99 employees did not use any AI applications with percentage it is 1.9% compared with. 0.3% of 1 the respondents from SMEs for who had nonemployees. Also, 5 the respondents from SMEs who had number of employees from 1-4 with percentage 1.4%. In the meantime, 3 respondents from SMEs who had 5-19 employees 0.8% and 1 the respondents from SMEs who had 99- 250 employees is 0.3%. Results also indicate that 4.7% of the 17 respondents from all number of employees categories did not use any AI applications.

Table 6.42: Cross-tabulation (Number of employees by application)

Number of Employees	**Applications**					**Total**
	none	1-2	2-3	3-4	5 and above	
Non	1	7	2	0	0	10

	0.3%	1.9%	0.5%	0	0	2.7%
1-4	5	11	7	2	2	27
	1.4%	3.0%	1.9%	0.5%	0.5%	7.4%
5-19	3	20	16	5	5	49
	0.8%	5.5%	4.4%	1.4%	1.4%	13.5%
20-99.	7	81	61	34	24	207
	1.9%	22.3%	16.8	9.3%	6.6%	56.9%
99-250.	1	32	16	16	6	71
	0.3%	8.8%	4.4%	4.4%	1.6%	19.5%
Total	17	151	102	57	37	364
	4.7%	41.5%	28.0%	15.7%	10.17%	100%

Cross-tabulation (Number of employees by features)

The results of the cross-tabulation for number of employees by time are presented in Table 6.43 below. The results indicate that 17 the respondents from SMEs who had number of employees from 20-99 employees used AI applications used extensively with percentage it is 4.7%, compared with 0.3% of 1 respondent from SMEs who had non workers and 2 respondents' employees from 1-4. with percentage is 0.5%. In the meantime, 4 the respondents from SMEs who had 5-19 employees 1.1% and 6 the respondents from SMEs who had 99- 250 employees is 1.6%. Results also indicate that 8.2% of the 30 respondents' highset percentage from all number of employees categories used AI applications used extensively. The results indicate that 37 the respondents from SMEs who had number of employees from 20-99 employees used AI applications used frequently as the highest percentage it is 10.2%, compared with 0.3% of 1 respondent from SMEs who had non workers and 5 respondents' employees from 1-4 with percentage it is 1.4%. In the meantime, 5 the respondents from SMEs who had 5-19 employees 1.4%. and 20 the respondents from SMEs who had 99- 250 employees is 5.5%. Results also indicate that 28.0% of the 102 respondents from all number of employees categories used AI applications used frequently. The results indicate that 63 the respondents from SMEs who had number of employees from 20-99 employees used AI applications used quite often with percentage it is 17.3%, compared with 0.5% of 2 respondents from SMEs for who had non workers. with 0.5% of 2 respondents from SMEs employees from 1-4 as well. In the meantime, 15 the respondents from SMEs who had 5-19 employees 4.1% and 14 the respondents from SMEs who had 99- 250 employees is 3.8%. Results also indicate that 26.4% of the 96 respondents from all number of employees categories used quite often. The results indicate that 67 the respondents from SMEs who had number of employees from 20-99 employees used AI applications rarely with percentage it is 18.4% compared with 1.1% of 4 respondent from SMEs for who had nonemployees. Also, 12 respondents from SMEs who had number of employees from 1-4 with percentage 3.3%. In the meantime, 19 the respondents from SMEs who had 5-19 employees 5.2% and 24 the respondents from SMEs who had 99-250 employees is 6.6%. Results also indicate that 34.6% of the 126 respondents from all number of employees categories used AI applications rarely. The results indicate that 23 the respondents from SMEs who had number of employees from 20-99 employees did not use any AI applications with percentage it is 1.9%, compared with. 0.5% of 2 the respondents from SMEs for who had nonemployees. Also, 6 the respondents from SMEs who had number of employees from 1-4 with percentage 6.3%. In the meantime, 6 respondents from SMEs who had 5-19 employees 1.6% and 7 the respondents from SMEs who had 99- 250 employees is 1.9%. Results also indicate that 12.1% of the 44 respondents from all number of employees categories did not use any AI applications.

Table 6.43: Cross-tabulation (Number of employees by features)

Number of Employees	**Features**					**Total**
	not used at all	**used rarely**	**used quite often**	**used frequently**	**used extensively**	
Non	2	4	2	1	1	10
	0.5%	1.1%	0.5%	0.3%	0.3%	2.7%
1-4	6	12	2	5	2	27
	1.6%	3.3%	0.5%	1.4%	0.5%	7.4%
5-19	6	19	15	5	4	49
	1.6%	5.2%	4.1%	1.4%	1.1%	13.5%
20-99	23	67	63	37	17	207
	6.3%	18.4%	17.3%	10.2%	4.7%	56.9%
99- 250.	7	24	14	20	6	71
	1.9%	6.6%	3.8%	5.5%	1.6%	19.5%
Total	44	126	96	68	30	364
	12.1%	34.6%	26.4%	18.7%	8.2%	100%

Cross-tabulation for Role

Cross-tabulation (Role by time)

The cross-tabulation results for the role by time are presented in Table 6.44 below. The results indicate that 24 the respondents from SMEs who had Business owner role used more than 5 hours AI applications with percentage it is 6.6%, compared with 1.4% of 5 respondent from SMEs who had Director role and 13 respondents SMEs who had Senior Manager with percentage is 3.6%. In the meantime, 28 the respondents from SMEs who had Manager percentage is 7.7% and 20 the respondents from SMEs who had Supervisor Role with percentage is 5.5%. Results also indicate that 27.7% of the 90 respondents' highset percentage from all number of employees categories used AI applications used more than 5 hours. The results indicate that 17 the respondents from SMEs who had Business owner role used 3-4 hours AI applications with percentage it is 4.7%, compared with 1.4% of 5 respondent from SMEs who had Director role and 10 respondents SMEs who had Senior Manager with percentage is 2.7%. In the meantime, 24 the respondents from SMEs who had Manager percentage is 6.6% and 14 the respondents from SMEs who had Supervisor Role with percentage is 3.8%. Results also indicate that 19.2% of the 70 respondents' highset percentage from all number of employees categories used AI applications used 3-4 hours. The results indicate that 21 the respondents from SMEs who had Business owner role used 2-3 hours AI applications with percentage it is 5.8%, compared with 0.5% of 2 respondent from SMEs who had Director role and 11 respondents SMEs who had Senior Manager with percentage is 3.0%. In the meantime, 28 the respondents from SMEs who had Manager percentage is 7.7% and 11 the respondents from SMEs who had Supervisor Role with percentage is 3.0%. Results also indicate that 20.1% of the 73 respondents' highset percentage from all number of employees categories used AI applications used 2-3 hours. The results indicate that 24 the respondents from SMEs who had Business owner role used 1-2 hours AI applications with percentage it is 6.6%, compared with 3.3% of 12 respondent from SMEs who had Director role and 11 respondents SMEs who had Senior Manager with percentage is 3.0%. In the meantime, 16 the respondents from SMEs who had Manager percentage is 4.4% and 7 the respondents from SMEs who had Supervisor Role with percentage is 1.9%. Results also indicate that 19.2% of the 70 respondents' highset percentage from all number of employees categories used AI applications used 1-2 hours. The results indicate that 15 the respondents from SMEs who had Business owner role less than 1 hour AI applications with percentage it is 4.1%, compared with

3.8% of 14 respondent from SMEs who had Director role and 12 respondents SMEs who had Senior Manager with percentage is 3.3%. In the meantime, 15 the respondents from SMEs who had Manager percentage is 4.1% and 5 the respondents from SMEs who had Supervisor Role with percentage is 1.4%. Results also indicate that 16.8%% of the 61 respondents' highset percentage from all number of employees categories used AI applications used less than 1 hour.

Table 6.44: Cross-tabulation (role by Time).

Role	Time					Total
	Less than 1 hour	1-2 hours	2-3 hours	3-4 hours	More than 5 hours	
Business owner	15	24	21	17	24	101
	4.1%	6.6%	5.8%	4.7%	6.6%	2.7.8%
Director	14	12	2	5	5	38
	3.8%	3.3%	0.5%	1.4%	1.4%	10.4%
Senior Manager	12	11	11	10	13	57
	3.3%	3.0%	3.0%	2.7%	3.6%	15.7%
Manager	15	16	28	24	28	111
	4.1%	4.4%	7.7%	6.6%	7.7%	30.5%
Supervisor	5	7	11	14	20	57
	1.4%	1.9%	3.0%	3.8%	5.5%	15.7%
Total	61	70	73	70	90	364
	16.8%	19.2%	20.1%	19.2%	27.7%	100%

Cross-tabulation (Role by frequency)

The cross-tabulation results for the role by frequency are presented in Table 6.45 below. The results indicate that 25 the respondents from SMEs who had Business owner role used AI applications several times a day with percentage it is 6.9%, compared with 1.9% of 7 respondent from SMEs who had Director role and 16 respondents SMEs who had Senior Manager with percentage is 4.4%. In the meantime, 29 the respondents from SMEs who had Manager percentage is 8.0% and 19 the respondents from SMEs who had Supervisor Role with percentage is 5.2%. Results also indicate that 26.4% of the 96 respondents' highset percentage from all number of employees categories used AI applications used several times a day. The results indicate that 23 the respondents from SMEs who had Business owner role used AI applications once a day with percentage it is 6.3%, compared with 2.2% of 8 respondent from SMEs who had Director role and 14 respondents SMEs who had Senior Manager with percentage is 3.8%. In the meantime, 26 the respondents from SMEs who had Manager percentage is 7.1% and 14 the respondents from SMEs who had Supervisor Role with percentage is 3.8%. Results also indicate that 23.4% of the 85 respondents' highset percentage from all number of employees categories used AI applications used once a day. The results indicate that 27 the respondents from SMEs who had Business owner role used AI applications a few times a month with percentage it is 7.4%, compared with 0.8% of 3 respondent from SMEs who had Director role and 8 respondents SMEs who had Senior Manager with percentage is 2.2%. In the meantime, 32 the respondents from SMEs who had Manager percentage is 8.8% and 11 the respondents from SMEs who had Supervisor Role with percentage is 3.0%. Results also indicate that 22.3% of the 81 respondents' highset percentage from all number of employees categories used AI applications used A few times a month. The results indicate that 16 the respondents from SMEs who had Business owner role used AI applications once a month with percentage it is 4.4%, compared with 2.2% of 8 respondent from SMEs who had Director role and 11 respondents SMEs who had Senior Manager with percentage is 3.0%. In the meantime, 16 the respondents from SMEs who had Manager percentage is 4.4% and 9 the respondents from SMEs who had Supervisor Role with percentage is 2.5%. Results also indicate that 16.5% of the 60 respondents' highset percentage from all number of employees categories used AI applications used once a month. The results indicate that 10 the respondents from SMEs who had Business owner role used AI applications for less than once a month with percentage it is 2.8%, compared with 3.3% of 12 respondent from SMEs who had Director role and 8 respondents SMEs who had Senior Manager with percentage is 2.2%. In the meantime, 8 the respondents from SMEs who had Manager percentage is 2.2% and 4 the respondents from SMEs who had Supervisor Role with percentage is 1.1%. Results also indicate that 11.5% of the 42 respondents' highset percentage from all number of employees categories used AI applications used less than once a month.

Table 6.45: Cross-tabulation (Role by frequency)

Role	**Frequency**					**Total**
	Less than once a month	Once a month	A few times a month	Once a day	Several times a day	
Business owner	10	16	27	23	25	101
	2.8%	4.4%	7.4%	6.3%	6.9%	27.8%

Director	12	8	3	8	7	38
	3.3%	2.2%	0.8%	2.2%	1.9%	10.4%
Senior Manager	8	11	8	14	16	57
	2.2%	3.0%	2.2%	3.8%	4.4%	15.7%
Manager	8	16	32	26	29	111
	2.2%	4.4%	8.8%	7.1%	8.0%	30.5%
Supervisor	4	9	11	14	19	57
	1.1%	2.5%	3.0%	3.8%	5.2%	15.7%
Total	42	60	81	85	96	364
	11.5%	16.5%	22.3%	23.4%	26.4%	100%

Cross-tabulation (Role by Level of Usage)

The cross-tabulation results for the role by level of usage are presented in Table 6.46 and in Figure 6.13 below. The results indicate that 9 the respondents from SMEs who had Business owner role used AI applications Used extensively a day with percentage it is 2.5%, compared with 0.8% of 3 respondent from SMEs who had Director role and 7 respondents SMEs who had Senior Manager with percentage is 1.9%. In the meantime, 12 the respondents from SMEs who had Manager percentage is 3.3% and 8 the respondents from SMEs who had Supervisor Role with percentage is 2.2%. Results also indicate that 10.7% of the 39 respondents' highset percentage from all number of employees categories used AI applications used extensively. The results indicate that 31 the respondents from SMEs who had Business owner role used AI applications used frequently a day with percentage it is 8.5%, compared with 2.5% of 9 respondent from SMEs who had Director role and 15 respondents SMEs who had Senior Manager with percentage is 4.1%. In the meantime, 36 the respondents from SMEs who had Manager percentage is 9.9% and 24 the respondents from SMEs who had Supervisor Role with percentage is 6.6%. Results also indicate that 31.6% of the 115 respondents' highset percentage from all number of employees categories used AI applications used frequently. The results indicate that 27 the respondents from SMEs who had Business owner role used AI applications used quite often with percentage it is 7.4%, compared with 0.8% of 3 respondent from SMEs who had Director role and 10 respondents SMEs who had Senior Manager with percentage is 2.8%. In the meantime, 25 the respondents from SMEs who had Manager percentage is 6.9% and 10the respondents from SMEs who had Supervisor Role with percentage is 2.75%. Results also indicate that 20.6% of the 75 respondents' highset percentage from all number of employees categories used AI applications used quite often. The results indicate that 29 the respondents from SMEs who had Business owner role used AI applications used rarely often with percentage it is 8.0%, compared with 5.8% of 21 respondent from SMEs who had Director role and 18 respondents SMEs who had Senior Manager with percentage is 4.9%. In the meantime, 31 the respondents from SMEs who had Manager percentage is 8.5% and 10 the respondents from SMEs who had Supervisor Role with percentage is 2.75%. Results also indicate that 29.9% of the 109 respondents' highset percentage from all number of employees categories used AI applications used rarely. The results indicate that 2 the respondents from SMEs who had Business owner role not used AI applications at all with percentage it is 1.4%, compared with 0.5% of 2 respondent from SMEs who had Director role and 7 respondents SMEs who had Senior Manager with percentage is 1.9%. In the meantime, 7 the respondents from SMEs who had Manager percentage is 1.9% and 5 the respondents from SMEs who had Supervisor Role with percentage is 1.4%. Results also indicate that 7.2%. of the 26 respondents' highset percentage from all number of employees categories not used AI applications.

Table 6.46: Cross-tabulation Role by level of usage)

Role	**Usage**					**Total**
	Not used at all	Used rarely	Used quite often	Used frequently	Used extensively	
Business owner	5	29	27	31	9	101
	1.4%	8.0%	7.4%	8.5%	2.5%	2.7.8%
Director	2	21	3	9	3	38
	0.5%	5.8%	0.8%	2.5%	0.8%	10.4%
Senior Manager	7	18	10	15	7	57
	1.9%	4.9%	2.8%	4.1%	1.9%	15.7%
Manager	7	31	25	36	12	111
	1.9%	8.5%	6.9%	9.9%	3.3%	30.5%
Supervisor	5	10	10	24	8	57
	1.4%	2.75%	2.75%	6.6%	2.2%	15.7%
Total	26	109	75	115	39	364
	7.2%	29.9%	20.6%	31.6%	10.7%	100%

Cross-tabulation (Role by application)

The cross-tabulation results for the role by application are presented in Table 6.47 below. The results indicate that 10 the respondents from SMEs who had Business owner role used AI applications more than 5 with percentage it is 2.75%, compared with 0.5% of 2 respondent from SMEs who had Director role and 5 respondents SMEs who had Senior Manager with percentage is 1.4%. In the meantime, 13 the respondents from SMEs who had Manager percentage is 3.6% and 7 the respondents from SMEs who had Supervisor Role with percentage is 1.9%. Results also indicate that 10.1%. of the 37 respondents' highset percentage from all number of employees categories used AI applications more than5. The results indicate that 16 the respondents from SMEs who had Business owner role used AI applications 3-4 with percentage it is 4.4%, compared with 1.4% of 5 respondent from SMEs who had Director role and 7 respondents SMEs who had Senior Manager with percentage is 1.9%. In the meantime, 18 the respondents from SMEs who had Manager percentage is 4.9% and 11 the respondents from SMEs who had Supervisor Role with percentage is 3.0%. Results also indicate that 15.7%. of the 57 respondents' highset percentage from all number of employees categories used AI applications 3-4. The results indicate that 31 the respondents from SMEs who had Business owner role used AI applications 2-3 with percentage it is 8.5%, compared with 2.2% of 8 respondent from SMEs who had Director role and 17 respondents SMEs who had Senior Manager with percentage is 4.7%. In the meantime, 33 the respondents from SMEs who had Manager percentage is 9.0% and 13 the respondents from SMEs who had Supervisor Role with percentage is 3.6%. Results also indicate that 28.0% of the 102 respondents' highset percentage from all number of employees categories used AI applications 2-3. The results indicate that 42 the respondents from SMEs who had Business owner role used AI applications 1-2 with percentage it is 11.5%, compared with 4.9% of 18 respondent from SMEs who had Director role and 24 respondents SMEs who had Senior Manager with percentage is 6.6%. In the meantime, 42 the respondents from SMEs who had Manager percentage is 11.5% and 25 the respondents from SMEs who had Supervisor Role with percentage is 6.9%. Results also indicate that 41.5% of the 151 respondents' highset percentage from all number of employees categories used AI applications 1-2. The results indicate that 2 the respondents from SMEs who had Business owner role used non any AI applications with percentage it is 0.5%, compared with 1.4% of 5 respondent from SMEs who had Director role and 4 respondents SMEs who had Senior Manager with percentage is 1.1%. In the meantime, 5 the respondents from SMEs who had Manager percentage is 1.4% and one the respondents from SMEs who had Supervisor Role with percentage is 0.3%. Results also indicate that 4.7% of the 17 respondents' highset percentage from all number of employees categories used non any AI applications.

Table 6:47: Cross-tabulation (Role by application)

Role	Application					Total
	None	1-2	2-3	3-4	More than 5	
Business owner	2	42	31	16	10	101
	0.5%	11.5%	8.5%	4.4%	2.75%	27.8%
Director	5	18	8	5	2	38
	1.4%	4.9%	2.2%	1.4%	0.5%	10.4%
Senior Manager	4	24	17	7	5	57
	1.1%	6.6%	4.7%	1.9%	1.4%	15.7%
Manager	5	42	33	18	13	111
	1.4%	11.5%	9.0%	4.9%	3.6%	30.5%
Supervisor	1	25	13	11	7	57
	0.3%	6.9%	3.6%	3.0%	1.9%	15.7%
Total	17	151	102	57	37	364
	4.7%	41.5%	28.0%	15.7%	10.1%	100%

Cross-tabulation (Role by Features)

Results concerning the cross-tabulation results for the role by features are described in Table 6.48 below. The results indicate that 10 the respondents from SMEs who had Business owner role used extensively AI applications with percentage it is 2.7%, compared with 0.8% of 3 respondent from SMEs who had Director role and 4 respondents SMEs who had Senior Manager with percentage is 1.1%. In the meantime, 9 the respondents from SMEs who had Manager percentage is 2.5% and 4 the respondents from SMEs who had Supervisor Role with percentage is 1.1%. Results also indicate that 8.2% of the 30 respondents' highset percentage from all number of employees categories used extensively AI applications. The results indicate that 17 the respondents from SMEs who had Business owner role used frequently AI applications with percentage it is 4.7%, compared with 2.2% of 8 respondent from SMEs who had Director role and 8 respondents SMEs who had Senior Manager with percentage is 2.2%. In the meantime, 19 the respondents from SMEs who had Manager percentage is 5.2% and 16 the respondents from SMEs who had Supervisor Role with percentage is 4.4%. Results also indicate that 18.7% of the 68 respondents' highset percentage from all number of employees categories used frequently AI applications. The results indicate that 27the respondents from SMEs who had Business owner role used quite often the AI applications with percentage it is 7.4%, compared with 0.8% of 3 respondent from SMEs who had Director role and 16 respondents SMEs who had Senior Manager with percentage is 4.4%. In the meantime, 37 the respondents from SMEs who had Manager percentage is 10.2% and 13 the respondents from

SMEs who had Supervisor Role with percentage is 3.6%. Results also indicate that 26.4% of the 96 respondents' highset percentage from all number of employees categories used quite often the AI applications. The results indicate that 9 the respondents from SMEs who had Business owner role did not use the AI applications at all with percentage it is 2.5%, compared with 1.6% of 6respondent from SMEs who had Director role and 8 respondents SMEs who had Senior Manager with percentage is 2.2%. In the meantime, 15 the respondents from SMEs who had Manager percentage is 4.1% and 6 the respondents from SMEs who had Supervisor Role with percentage is 1.6%. Results also indicate that 12.1% of the 44 respondents' highset percentage from all number of employees categories did not use the AI applications at all.

Table 6.48: Cross-tabulation (Role by features).

Role	**Features**					**Total**
	Not used at all	Used rarely	Used quite often	Used frequently	Used extensively	
Business owner	9	38	27	17	10	101
	2.5%	10.4%	7.4%	4.7%	2.7%	2.7.8%
Director	6	18	3	8	3	38
	1.6%	4.9%	0.8%	2.2%	0.8%	10.4%
Senior Manager	8	21	16	8	4	57
	2.2%	5.8%	4.4%	2.2%	1.1%	15.7%
Manager	15	31	37	19	9	111
	4.1%	8.5%	10.2%	5.2%	2.5%	30.5%
Supervisor	6	18	13	16	4	57
	1.6%	4.9%	3.6%	4.4%	1.1%	15.7%
Total	44	126	96	68	30	364
	12.1%	34.6%	26.4%	18.7%	8.2%	100%

An analysis of demographic features was conducted to examine whether demographic characteristic affects individuals' proception regarding the adoption and use of AI /digital technologies by owners/managers in Jordanian SMEs. The initial correlation was analyzed to determine if there is any evidence of a relationship between demographic characteristics and perception. The results of this analysis, as shown in Table 6.49, clearly show there is a correlation between gender and perception (r= 0.145**), age and perception (r= 0.357**), qualifications(r=0.125*), experience and perception (r=.000), industry and perception (r=. 0.040), Employees and perception (r= 0.578**), Role and perception (r= 0.349**). The correlation loadings were divided into three categories: 0.30 = minor; 0.40 = substantial; and

0.50 = significant. (Tabachnick & Fidell 2001). It appears that results for age, experience, employees, and role provide evidence for solid relationship levels.

Correlation refers to the degree to which two variables are related to each other. Perception refers to an individual's subjective understanding and interpretation of a given situation or phenomenon. In this study, there is a correlation between demographics and perceptions among SMEs in Jordan, but the correlation is weak to moderate. The results you mentioned in Table 6.49 indicate that there are significant correlations between specific demographics (gender, age, qualifications, industry, employees, and role) and perceptions among SMEs in Jordan, but these correlations are not strong or perfect. A correlation coefficient (r) ranges from -1 to 1, where -1 indicates a perfect negative correlation, 0 indicates no correlation, and 1 indicates a perfect positive correlation. A weak correlation typically ranges between 0.1 and 0.3, a moderate correlation between 0.3 and 0.5, and a strong correlation between 0.5 and 1.0 (Cohen, 1988)

The correlation between gender and perception (r=0.145) is considered weak, indicating that there is some relationship between gender and perception, but it is not a strong one. Similarly, the correlations between qualifications (r=0.125) and industry (r=0.040) and perception are also weak. On the other hand, the correlations between age and perception (r=0.357), employees and perception (r=0.578), and role and perception (r=0.349) are considered moderate, suggesting that there is a significant relationship between these demographics and perceptions, but it is not a strong one. The lack of strong or perfect correlations between demographics and perceptions can be attributed to several factors. For example, perceptions are subjective and can be influenced by a variety of factors beyond demographics, such as personal experiences, cultural norms, and individual preferences. Additionally, the sample size, sampling method, and measurement tools used in the study can also affect the strength of the correlations (Cohen, 1988; Field, 2013). It is worth noting that the correlations mentioned above are statistically significant, meaning that they are unlikely to occur by chance. Therefore, even though the correlations may not be strong, they are still meaningful and can provide valuable insights into the relationship between demographics and perceptions among SMEs in Jordan. In the case of SMEs in Jordan, research has shown that there is a weak to moderate correlation between demographics and perceptions. For example, a study by Al-Qatawneh et al. (2018) found that there was a weak correlation between age and the perception of financial risk among SMEs in Jordan. Another study by Al-Madi et al. (2015) found that there was a moderate correlation between education level and the perception of the impact of government regulations on SMEs in Jordan. One possible reason for the weak to moderate correlation between demographics and perceptions is the diversity within the SME sector in Jordan. SMEs in Jordan vary in terms of size, industry, and location, which can influence the perceptions of business owners and managers.

Additionally, individual differences in personality, values, and experiences can also contribute to the diversity of perceptions within the SME sector. Another possible reason is the complex interplay between demographics and perceptions. While demographics can influence perceptions, perceptions can also shape demographics. For example, an individual's perception of a certain industry may influence their decision to pursue a career in that industry, which in turn affects the demographic makeup of that industry. The weak to moderate correlation between demographics and perceptions among SMEs in Jordan suggests that perceptions are shaped by a range of factors beyond just demographic characteristics. It is important for researchers and policymakers to consider the diversity of perceptions within the SME sector and to take a holistic approach to understanding the drivers of business success and growth.

Table 6.49: Correlation between demographics and perception.

Variables	**Gender**	**Age**	**Qualifications**	**Experience**	**Industry**	**Employees**	**Role**	**perception**
Gender	1							
Age	.257**	1						
Education	-.005	-.020	1					
Experience	.089	.152**	.071	1				
Industry	.050	.020	.025	.011	1			
Employees	.050	.185**	.047	.259**	.007	1		
Role	.072	.089	-.059	.183**	-.031	.377**	1	
perception	.145**	.357**	.125*	.626**	.040	.578**	.349**	1

**. Correlation is significant at the 0.01 level (2-tailed).
*. Correlation is significant at the 0.05 level (2-tailed).

6.6 Data Screening fix the collected data

The data undergo screening to find data entry errors (Aminu & Shariff, 2014) to avoid incorrect results and findings (Hair et al., 2006: Field, 2005). To modify the collected data. This study conducted data screening which is is an essential aspect of any multivariate analysis, laying the foundation for the quantitative study (Babagana, Mat & Ibrahim 2019; Abubakar & Muhammad Anka, 2022). The study sample comprises 401 owners/managers in SMEs in Amman, the capital of Jordan. After data screening, data from 364 owners/managers in SMEs were used to test the model. Confirmatory factor analyses for all instruments were conducted before examining the model, and they were all verified. Data screening was done to ensure that no incorrect data were input into SPSS (Harmandaoğlu Baz & Cephe, 2022). This study omitted 37 respondents that were acquired from owners/managers in SMEs in Amman; it has been discovered that there are some excessive, missing, and incomplete values. 364 out of 401 data points from those instruments were taken from the analysis and used in the study. The data utilized in the study are now as precise and comprehensive as possible, thanks to this method (Leong & Austin, 2006). The analysis appeared for any outliers in the data setting. No such concerns were observed.

6.7 Normality

The statistical testing normality is sensitive to the size of research data; it is recommended to check the histogram with skewness and kurtosis values to evaluate univariate normality (Field, 2005). Table 6.50 shows the skewness and kurtosis of the study variables. According to Haie et al. (2006), the accepted range of skewness and kurtosis is between -2.58 and +2.58. All the skewness and kurtosis values in Table 6.50 below fall within scope except one Kurtosis value which refers to the profitability variable. Many statistical techniques used for data analysis, such as correlation, regression, t-tests, and analysis of variance, make normality assumptions. According to the central limit theorem, deviation from normality is not a severe problem when the sample size is 100 or more observations (Mishra, Pandey, Singh, Gupta, Sahu & Keshri, 2019). The histograms, as well as the absolute values of skewness and kurtosis, are what determine the normality of the data for samples more prominent than 300. For determining significant normalcy, either a total skewness value ≤2 or an absolute kurtosis (excess) ≤4 may be utilized as reference values (Kim, 2013). A histogram represents an estimation of a continuous variable's probability distribution. We can assume normally distributed data if the graph is substantially bell-shaped and symmetric about the mean (Barton & Peat, 2014).

Table 6.50 Skewness and Kurtosis Statistics for the Study Variables (N=364)

Scale	**Skewness**	**Kurtosis**
Strategy	-.663	1.125
Knowledge	-.959	2.152
Infrastructure	-.928	1.266
Managerial support	-.770	1.282
Training	-.702	1.060
Reward system	-.509	.777
Government support	-1.210	2.156
Government regulations	-.642	.180
Competitive pressure	-.625	.760
Peers ‘supports	-.860	1.049
Social network	-.434	.873
Religious beliefs	-.324	-.473
Usage	-.048	-.489
Performance	-1.025	1.174
Productivity	-1.206	1.810
Profitability	-1.282	3.036
Customers satisfaction	-1.095	1.462
Market share	-1.077	1.509
Sales improvement	-.986	1.083
Perceptions	-.825	1.167

6.8 Checking Assumptions

The statistical analysis findings used to verify the assumptions show that there are no issues with outliers or multicollinearity and that there is also no autocorrelation. The histogram, the normal probability plot of the residuals, and the plot of standardized residuals versus standardized predicted values (ZRESID against ZPRED) were all examined in the study. Relationships between residuals and predicted values of dependent variables are displayed in scatterplots. This figure makes testing the linearity and homoscedasticity of the residual assumptions easy. The graph should resemble a haphazard collection of dots uniformly spaced around zero. Any curve in this graph indicates that the data have likely violated the assumption of linearity. The standardized residuals are plotted against the standardized predicted values in Figure 6.13. The points are at random and evenly distributed throughout, most of which are evenly distributed around zero. Although some residuals are along the plots, the homoscedasticity condition is not violated. There is no curved relationship in the plots, nor do the points resemble a funnel. The graphic pattern demonstrates a situation in which the linearity and homoscedasticity presumptions have been satisfied.

Regression standardized predicted values

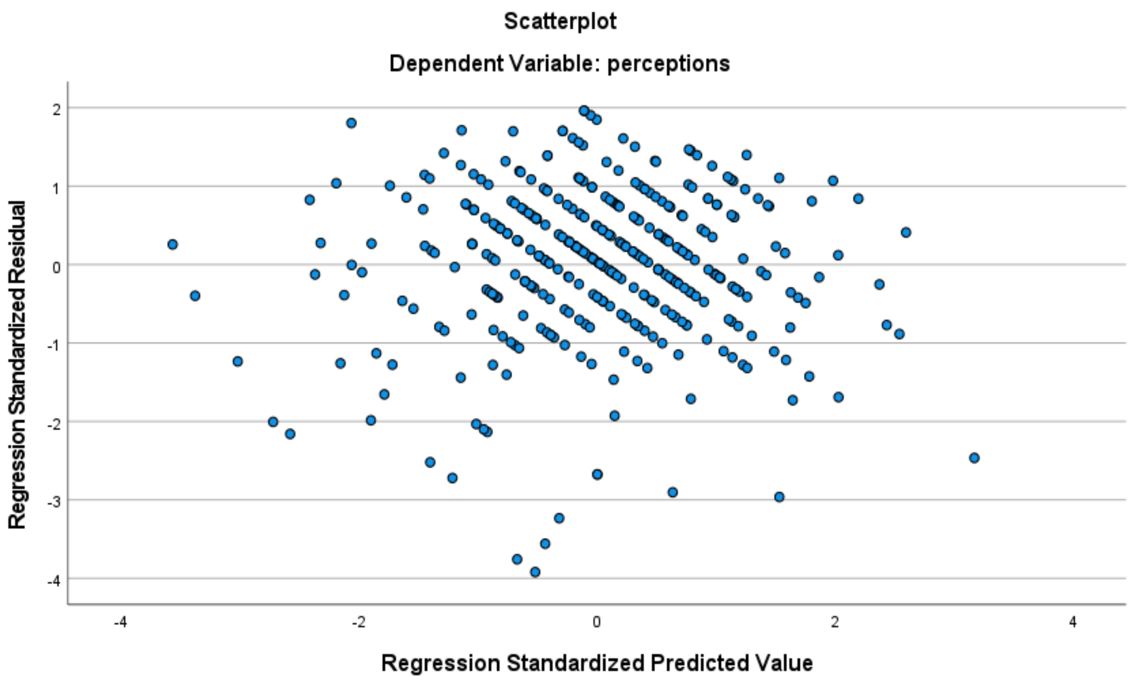


Figure 6.1: Plot of standardized residuals against standardized predicted values

Analysis was carried out using histogram and normal probability plots, which show whether residuals are normally distributed, to test the normality of the residuals. Figure 6.14: Histogram of normally distributed residuals. The histogram should resemble a bell-shaped curve for a normal distribution. A histogram for this study reveals that the distribution is essentially normal, despite a little deficit of residuals in the middle. The histogram demonstrates that the data is normally distributed as a result. The residuals' normal probability plots were looked at to validate the normality assumptions. A straight line represents a normal distribution in the graph's probability plot.

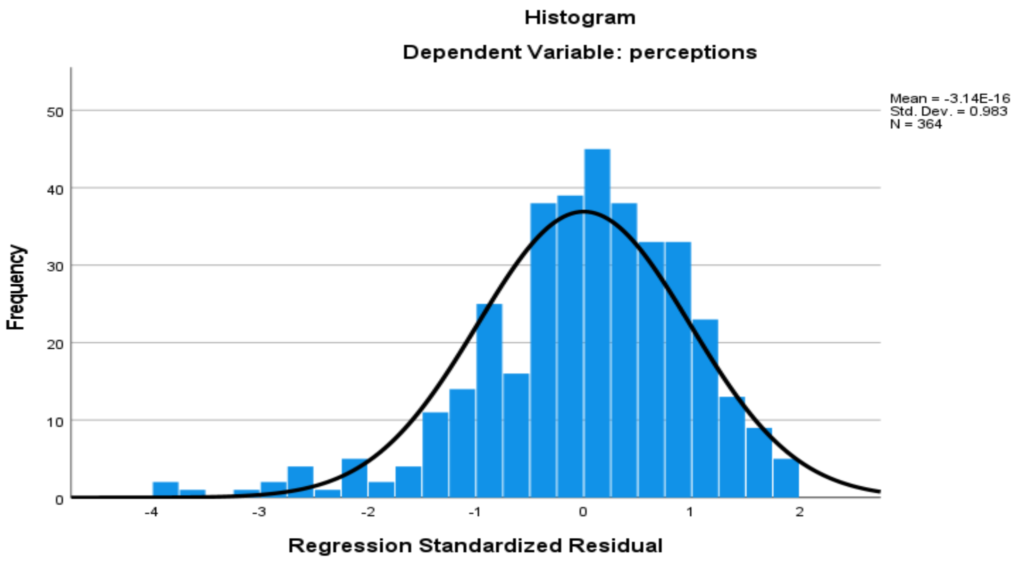


Figure 6.2: Histogram of normally distributed residuals

A data collection with perfectly normally distributed points would have all of its points on a straight line. This study's histogram and normal probability plots exhibit a largely normal distribution. Hence the assumption is not violated. Figure 6.15 displays a normal probability-probability (P-P) plot of the regression standardised residuals for this study, while Figure 6.14 displays a histogram of normally distributed residuals. A normal distribution can be shown in a histogram and normal probability graphs.

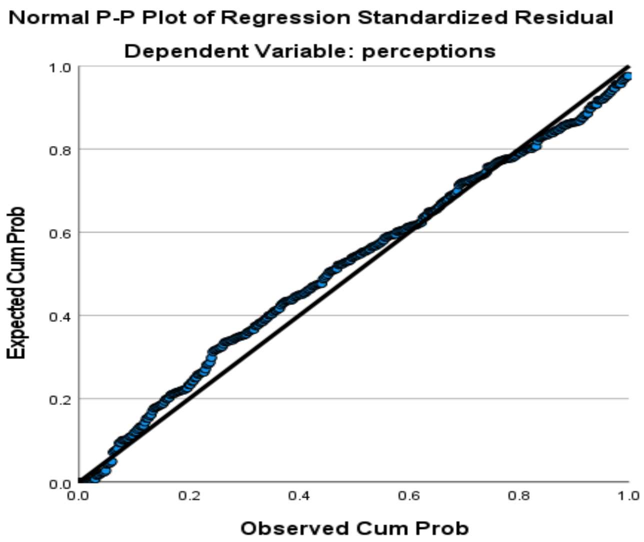


Figure 6.3: Normal P-P plot of regression standardized residual

6.9 Reliability and Validity of the Study

When analysing the literature on a particular topic, the study needs to be assessed for the rigour and integrity of the measurements used. It is best practice to conduct and write about research to provide detailed information about reliability and validity (Dodgson, 2021; Duckett, 2021). The methods used to describe the measurement of reliability and validity are sometimes described explicitly using either statistical examination or other recognized forms of testing (Duckett, 2021). However, here we focus mainly on their use for evaluating measurement according to quantitative research methodology. A questionnaire pre-test is highly recommended to ensure that all items are clear and understood (Sekaran & Bougie, 2016). The critical method for establishing if the factors are valid and reliable is to contact a pilot study. According to several studies (Chetwynd, 2022; Urbina & Monks, 2021; Talukder et al., 2014; Mann et al., 2009; Aladwani, 2006), there are different ways to validate the questionnaire. The questionnaire used in the measurement was based on valid items from previous studies. Taylor (2021) recommended using existing Cronbach's alpha scores to measure the quality of a questionnaire. Cronbach's alpha is the most popular reliability test and is generally considered reliable if the correlation coefficient is 0.7 or higher (Chetwynd, 2022; Sekaran & Bougie, 2016; Urbina & Monks, 2021; Hair et al., 2006).

Reliability of the Study

Researchers attempt to use the most accurate measurement as rigorously as possible. They employ previously established instruments rather than researcher-created instruments (Chetwynd, 2022). The reliability of an instrument or questionnaire concerns the consistency, stability, and dependability of the scores (Hancock et al., 2010; Ramezani et al., 2022). While Cronbach's alpha is the most commonly used reliability estimate (Hogan et al., 2000; Kaplan, 2004; Ramezani et al., 2022), it is best suited for assessing items scored in multiple answer categories. The instrument is generally considered reliable if the correlation coefficient is 0.7 or higher (Urbina & Monks, 2021). According to Hair et al. (2006), construct reliability should be 0. 7 or higher, which is the standard threshold of reporting construct reliability (Nunnally, 1978; Hair et al., 1998). Reliability values between .70 and .80 are considered respectable (DeVellis, 2003; DeVellis, & Thorpe, 2021). According to Revelle and Condon (2019) reliability refers to the reproducibility of the study findings, should the same measurement questionnaire be applied in different situations. Reliability measures an instrument's equivalence, stability, and internal consistency (Bannigan & Watson, 2009). Revelle and Condon (2019) stated that the basic concept of reliability is very simple: observed scores reflect an unknown mixture of signal and noise. Twenty scales were employed in the survey questionnaire to measure the constructs proposed, and each scale has five items. The reliability was run on SPSS v27, and results are presented in Table 6.51 which shows Cronbach's alpha (a) value for each variable.

Table 6.51 Cronbach's alpha reliability Results

Factor	Cronbach's alpha	No of Items	Comments
(1) Technology strategy	.810	5	Very Good Reliability
(2) Employees IT knowledge	.813	5	Very Good Reliability
(3) Technology infrastructure	.820	5	Very Good Reliability
(4) Managerial support	.808	5	Very Good Reliability
(5) Training	.811	5	Very Good Reliability
(6) Reward system	.813	5	Very Good Reliability
(7) Government support	.815	5	Very Good Reliability
(8) Government regulations	.817	5	Very Good Reliability
(9) Competitive pressure	.815	5	Very Good Reliability

(10) Peer support	.812	5	Very Good Reliability
(11) Social network	.817	5	Very Good Reliability
(12) Religious beliefs	.813	5	Very Good Reliability
(13) Perception	.794	5	Respectable Reliability
(14) Usage	. 812	5	Very Good Reliability
(15) Performance	.809	5	Very Good Reliability
(16) Productivity	.801	5	Very Good Reliability
(17) Profitability	.807	5	Very Good Reliability
(18) Market share	.802	5	Very Good Reliability
(19) Customer satisfaction	.806	5	Very Good Reliability
(20) Sales improvement	.799	5	Respectable Reliability

Validity of the Study

Validity tests the interpretation of study instruments and refers to whether they measure what they have been reported to be measuring, as supported by evidence and theory in the topic area of investigation (Clark & Watson, 2019). It is the basis on which the research instrument is built. The pilot study was conducted to test the questionnaire's validity and assess whether the (Cavana, Delahaye & Sekaran, 2001; Md-Sidin, Sambasivan & Ismail, 2010; Fiksenbaum, 2013). Construct validation is based on the assessed variables' theory (Chetwynd, 2022). For face validity, researchers may draw on the existing literature or their capabilities without having any outside validation (Mostert, 2022). There is not a lack of published research instruments, but the instrument needed for a validation study is highly considered, used comparatively frequently, and has predictable results (Bannigan & Watson, 2009). Many techniques can be implemented while verifying construct validation to include in this study. In short, construct validity is used to assess the bridge between the theoretical framework that undergirds the measurement questionnaire' and what the questionnaire measures in the study (Chetwynd, 2022). Western and Rosenthal (2003) stated "A statement about the [construct] the validity of an instrument is a statement regarding the extent to which its observed relations with measures of other variables match theoretical predictions approximately how it should be associated with those variable" construct validation is never complete, but the proof of the instrument becomes stronger as it is applied in multiple settings, each use increasing its validity (Clark & Watson, 2019). Researchers create their instruments; it is suggested that various testing methods are used to demonstrate validity (Chetwynd, 2022). The researchers must provide enough evidence to the reader so that reliability and validity can be measured (Wambach, 2018). To get evidence of convergence and discriminant validity of a scale, use SPSS to run exploratory factor analysis and used it is loading to calculate Average Variance Extracted (AVE) and reliability through Cronbach's alpha. This analysis also employed convergent and discriminant validity to measure the validity of the study instruments. As shown in Table 6.52, all factor loadings range from 0.480 to .848, which are sufficient for the purposes of this study. The items under each construct were loaded heavily within the defined constructs; this provides evidence for the constructs' convergent validity. Discriminant validity is regard as sufficient when constructs have an average variance extracted (AVE) loading greater than 0.50, meaning that at least 50% of the measurement variance is taken by the constructs (Kim & Garrison, 2009). Table 6.45 illustrates that all constructs demonstrated an AVE score more significant than the recommended minimum score of 0.50. It is confirmed that the instrument has achieved an acceptable level of discriminant validity.

Table 6.52 Cronbach's alpha reliability Results

Factor	Factor Loading	Cronbach's alpha	AVE
Technology strategy		.810	0.779
Technology strategy1 Technology strategy2 Technology strategy3 Technology strategy4 Technology strategy5	.708 .722 .437 .649 .520	.	
Employees IT knowledge		.813	0.797
Employees IT knowledge1 Employees IT knowledge2 Employees IT knowledge3 Employees IT knowledge4 Employees IT knowledge5	.757 .773 .656 .588 .406		
Technology infrastructure		.820	0.612
Technology infrastructure1 Technology infrastructure2 Technology infrastructure3 Technology infrastructure4 Technology infrastructure5	.593 .700 .670 .613 .779		
Managerial support		.808	0.634

Managerial support1 Managerial support2 Managerial support3 Managerial support4 Managerial support5	.499 .451 .388 .397 .274		
Training		.811	0.709
Training1 Training2 Training3 Training4 Training5	.564 .716 .446 .685 .522		
Reward system		.813	0.624
Reward system1 Reward system2 Reward system3 Reward system4 Reward system5	.396 .220 .409 .599 .335		
Government support		.815	0.846
Government support1 Government support2 Government support3 Government support4 Government support5	.623 .739 .727 .720 .771		
Government regulations		.817	0.833
Government regulations1 Government regulations2 Government regulations3 Government regulations4 Government regulations5	.600 .702 .706 .762 .706		
Competitive pressure		.815	0.644
Competitive pressure1 Competitive pressure2 Competitive pressure3 Competitive pressure4 Competitive pressure5	.521 .476 .375 .283 .424		
Peer support		.812	0.723
Peer support1 Peer support2 Peer support3 Peer support 4 Peer support5	.384 .568 .584 .585 .497		
Social network		.817	0.798

Social network1 Social network2 Social network3 Social network4 Social network5	.718 .676 .498 .721 .576		
Religious beliefs		.813	0.734
Religious beliefs 1 Religious beliefs 2 Religious beliefs 3 Religious beliefs 4 Religious beliefs 5	.441 .545 .591 .563 .558		
Perception		.794	0.786
Perception1 Perception2 Perception3 Perception4 Perception5	.743 .565 .551 .690 .541		
Usage		.812	0.856
Time Frequency Level Types Features	.729 .804 .626 .737 .773		
Performance		.809	0.815
Performance1 Performance2 Performance3 Performance4 Performance5	.590 .718 .727 .636 .655		
Productivity		.801	
Productivity1 Productivity2 Productivity3 Productivity4 Productivity5	.758 .736 .772 .817 .726		
Profitability		.807	0.793
Profitability1 Profitability2 Profitability3 Profitability4 Profitability5	.634 .685 .658 .671 .690		
Customer satisfaction		.802	0.779

Customer satisfaction1 Customer satisfaction2 Customer satisfaction3 Customer satisfaction4 Customer satisfaction5	.687 .762 .708 .742 .657		
Market share		.806	0.806
Market share1 Market share2 Market share3 Market share4 Market share5	.635 .716 .649 .718 .668		
Sales Improvement		.799	0.773
SalesImprovement1 SalesImprovement2 SalesImprovement3 SalesImprovement4 SalesImprovement5	.658 .666 .661 .701 .660		

6.10 Exploratory factor analysis

Exploratory factor analysis (EFA)is a complicated and multivariate statistical technique commonly used in information systems, social science, and psychology education (Taherdoost, Sahibuddin & Jalaliyoon, 2022). Factor analysis (FA) is a powerful instrument utilized in developing, refining, and evaluating tests, scales, and measures (Williams, Brown et al., 2010). Factor analysis is divided into Factor analysis is split into two main types, namely, Exploratory Factor Analysis (EFA) and Confirmatory Factor Analysis (CFA) (Williams, Brown et al. 2010). The researcher has no expectations of the number of factors. Exploratory Factor Analysis is used. As the title suggests, it allows the investigator to investigate the main variables to create a theory or model from a relatively large set of latent elements often represented by a group of items (Henson & Roberts, 2006; Taherdoost, Sahibuddin & Jalaliyoon, 2022). CFA, as a form of structural equation modelling (SEM), is applied to test the proposed theory by the researcher or model. In contrast to EFA, CFA has assumptions and expectations based on prior models and theories about the number of constructs and which construct theories or models best fit (Williams, Brown et al. 2010). EFA was applied for many applications, including finding relationships between activity participation variables (Pitombo, E.Kawamoto et al. 2011). Objectives of Exploratory Factor Analysis (Pett, Lackey et al. 2003; Thompson 2004) are: reduction of number of factors (variables), Assessment of multicollinearity among factors which are correlated, Unidimensionality of constructs evaluation and detection, evaluation of construct validity in a survey, examination of factors (variables) relationship or structure, development of theoretical constructs, prove proposed theories. Although the sample size is a significant issue FA, there are different ideas and several guiding rules of literature. General guides include (Tabachnick and Fidell 2001)'s rule of thumb that suggests having at least 300 cases are needed for factor analysis. (Comrey 1973) stated in his guide to sample sizes: 100 as poor, 200 as fair, 300 as good, 500 as very good, and 1000 or more as excellent. This Study using the EFA method is thar the sample of he this study is significant. EFA is generally thought of as more of a theory generating rather than theory – testing procedure (Stevens, 2009). Moreover, EFA is data driven rather than theory or hypothesis driven (Brown, 2006). This study used SPSS 27.0 served to conduct the EFA. All scales of the search model were analyzed one by one, and details of the validation process and outcomes are discussed in the following subsections. In exploratory factor analysis (EFA), the sample size for the study, the correlation matrix test Scale as one of the most popular statistical techniques (Henson and Roberts 2006), is used to determine the relationships between variables and Kaiser-Meyer-Olkin (KMO) and Bartlett's Test.

Sample Size for Study

Even though the sample size is a crucial issue in factor analysis (FA), there are various theories and several general guidelines in the literature (Gorsuch, 1997; Tabachnick & Fidell, 2001; Hogarty, Hines, Kromrey, Ferron & Mumford, 2005). The rule of thumb proposed by Tabachnick and Fidell (2001) states that at least 300 examples are required for factor analysis. The recommendation to use sample sizes of 100 or more was made by (Hair, Black, Babin, Anderson & Tatham, 2011). According to Comrey (1973), 100 is considered poor, 200 is fair, 300 is acceptable, 500 is very good, and 1,000 or more is considered excellent. Hogarty et al. (2005) highlighted this lack of unanimity and claimed that these "disparate guidelines have not served researchers well." According to other research like Guadagnoli and Velicer (1988), smaller sample numbers are required for solutions with correlation coefficients >0.80. In contrast, Sapnas and Zeller's (2002) argument argued that even 50 cases might be sufficient for factor analysis. According to Costello and Osborne (2005), a more significant sample can be used to test the validity of the factor structure and individual items if any of the following issues with the data arise: Even though it is unlikely to occur inaccurate data, item communalities of

0.8 or more are considered to be "high". The item's commonality will be less than 0.40 if it is unrelated to other objects or if another construct has to be investigated. The minimal loading of an item with no cross-loadings should be 0.50 or higher (Comery & Lee, 1992). A construct with fewer than three items is typically unstable and weak; five elements that significantly load (0.50 or better) are preferred and signify a stable component (Taherdoost, Sahibuddin & Jalaliyoon, 2022). Hence, the sample size for this study is 364 participants and agree with opinions such as Comrey (1973), Tabachnick and Fidell (2001), Hair, Black, Babin, Anderson & Tatham, 2011).

Correlations Matrix

One of the most well-liked statistical methods uses a correlation matrix to ascertain the correlations between variables (Henson & Roberts 2006). Checking for correlation coefficients greater than 0.30 in the correlation matrix was advised by (Tabachnick & Fidell 2001). Or, in a practical sense, it would mean that a third of the variables share too much variance, making it difficult to determine whether the variables are correlated with each other or the dependent variable (multicollinearity). This is indicated by a loading of 0.3, which means that the factors account for about 30% of the relationship within the data (Williams, Onsman & Brown, 2010). Categorized the correlation loadings as 0.30 = minimal, 0.40 = important, and 0.50 = practically. If the correlation is less than 0.30, then it should be reconsidered if FA is the proper approach to be used for the research (Tabachnick & Fidell 2001). If the correlation matrix is an identity matrix (there is no relationship among the items) (Kraiser 1958), EFA should not be applied. The correlation loadings were divided into three categories: 0.30 = minor; 0.40 = substantial; and 0.50 = significant. If the correlations are less than 0.30, it should be re-examined whether FA is the best method for the study (Tabachnick & Fidell 2001). EFA should not be used if the correlation matrix is an identity matrix (i.e., there is no association between the elements) (Taherdoost, Sahibuddin & Jalaliyoon, 2022).

Kaiser-Meyer-Olkin (KMO) and Bartlett's Test

Test various tests must be performed to determine whether the sample is adequate and whether the data are suitable for factor analysis before the constructs are extracted (Taherdoost, Sahibuddin & Jalaliyoon, 2022). The researcher receives information about the grouping of survey items through sampling adequacy; the constructions under research can be better understood by organizing the elements into a collection of interpretable factors. The strength of an item's association with other items in the EFA correlation matrix is assessed by measures of sampling adequacy (Taherdoost, Sahibuddin & Jalaliyoon, 2022). Kaiser-Meyer-Olkin (KMO) analysis can determine the sampling's suitability (Kaiser, 1970). KMO is advised when the case to variable ratio is less than 1:5. It varies from 0 to 1, with 0.50 being deemed appropriate for FA (Tabachnick & Fidell 2001). According to Netemeyer, Bearden and Sharma (2003) KMO correlation of 0.60 to 0.70 or higher is deemed sufficient for assessing the output of an EFA. The chi-square output from Bartlett's test of sphericity must be substantial, it shows that the matrix is not an identity matrix, hence factor analysis should be appropriate if it is significant (Tabachnick & Fidell 2001). Researchers can proceed with the FA if the KMO suggests sample adequacy and Bartlett's test of sphericity reveals the item correlation matrix is not an identity matrix (Netemeyer, Bearden & Sharma, 2003; Taherdoost, Sahibuddin, & Jalaliyoon, 2022). The factor loading of scale items for technological strategy was investigated; low factor loading items should be repressed since they have a factor loading below 0.4. The recommended cut-off factor loading of 0.5 in this thesis ensured that all variables had application (Hair et al., 2006). (Table 6.48 demonstrates that all five of the loading values are more than the cut-off level of 0.5.

Extraction of Factors

Principal components analysis (PCA), principal axis factoring (PAF), image factoring, maximum likelihood, alpha factoring, unweighted least squares, generalized least squares, and canonical correlation analysis are a few techniques for extracting factors (Thompson, 2004; Costello & Osborne, 2005). However, principal axis factoring and principal component analysis are frequently employed in studies (Taherdoost, Sahibuddin, & Jalaliyoon, 2022). The use of PCA and PAF is hotly debated among analysts (Henson & Roberts, 2006). According to Thompson (2004), PCA is frequently employed because it is often the default approach in statistical software. PCA is advised to be employed when there is no prior theoretical foundation or model. Pett, Lackey and Sullivan (2003) suggested employing PCA while developing the first EFA solutions. Costello and Osborne (2005) claim that factor analysis is superior to principal component analysis, which is just a data reduction technique. The PCA is helpful if a researcher initially constructs an instrument with several items and is interested in lowering the number of items (Gorsuch, 2013; Taherdoost, Sahibuddin, & Jalaliyoon, 2022).

The below sections will be employed the Correlations Matrix, Kaiser-Meyer-Olkin (KMO) and Bartlett's Test and Extraction of factors as principal components analysis (PCA) for all independent variables.

Analysis for Technology strategy Scale (TS)

The findings for correlation coefficients between items for the technology strategy are provided in Table 6.53. The analysis of technology strategy Scale is 0.138 to 1.000, and positive correlation is calculated on a scale from 0.1 to 1.0. Week positive correlation would be in the range of 0.1 to 0.3. it appears that technology strategy scale has week positive correlation. A modest positive correlation would fall between 0.1 and 0.3. The correlation loadings were categorized by Taherdoost, Sahibuddin, and Jalaliyoon (2022) as 0.30 = little, 0.40 = considerable, and 0.50 = practically. According to Hair, Black, Babin, Anderson, and Tatham (2011), as well as Tabachnick and Fidell (2001), it is recommended to reconsider using FA if the correlations are less than 0.30 (Hair, Black, Babin, Anderson, and Tatham, 2011). which typically falls below 0.3. This suggests that they are not appropriate for factor analysis (FA) (Coakes, 2005). EFA should not be used if the correlation matrix is an identity matrix (i.e., there is no relationship between the items) (Kraiser, 1970).

Table 6.53 Correlations Matrix for Technology strategy

		ST1	ST2	ST3	ST4	ST5
Correlations	ST1	1	.495**	.226**	.143**	.138**
	ST2	.495**	1	.342**	.197**	.180**
	ST3	.226**	.342**	1	.314**	.138**
	ST4	.143**	.197**	.314**	1	.265**
	ST5	.138**	.180**	.138**	.265**	1

**. Correlation is significant at the 0.01 level (2-tailed).
*. Correlation is significant at the 0.05 level (2-tailed).

KMO and Bartlett's Test for Technology strategy Scale

As shown in Table 6.65, the results revealed that for KMO correlation items for the Technology strategy is 0.648. The result above the minimum acceptable level of 0.60 (Coakes et al., 2006) Test of Bartlett's test of sphericity (chi-square = 223.045) was highly significant at p< 0.000. indicating adequate nature of relations between the variables. The data therefore appropriate.

Table 6.54 KMO and Bartlett's Test for Technology strategy Scale

KMO and Bartlett's Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.648
Bartlett's Test of Sphericity	Approx. Chi-Square	223.045
	df	10
	Sig.	.000

Factor Loading for Technology strategy Scale

Factor Loading of scale items for technology strategy was examined. Principal Component Analysis (PCA)is frequently employed because it is often the default approach in statistical software (Thompson, 2004). Factor loading below 0.4 are considered low and low- items should be suppressed (Field, 2005). In this study, the recommended cut oof factor loading of 0.5 ensured that all variables had practical significant (Hair et al.2006). As shown in Table 6.55, the loading values of all five items exceed the cut-off level of 0.50.

Table 6.55 Factor Loading for Technology strategy Scale

Component Matrix

Items	**Component**
	1
ST1	.669
ST2	.754
ST3	.656
ST4	.576
ST5	.471

Extraction Method: Principal Component Analysis (PCA)

a. 1 component extracted.

Analysis for Employees IT Knowledge Scale (EK)

The findings for correlation coefficients between items for the employees' IT Knowledge are provided in Table 6.56. The analysis of employees' IT knowledge Scale is 0. 078 to 1.000, and positive correlation is calculated on a scale from 0.1 to 1.0. Week positive correlation would be in the range of 0.1 to 0.3. it appears that Employees IT Knowledge Scale has week correlation. According to Hair, Black, Babin, Anderson, and Tatham (2011), as well as Tabachnick and Fidell (2001), it is recommended to reconsider using FA if the correlations are less than 0.30 (Hair, Black, Babin, Anderson, and Tatham, 2011). which typically falls below 0.3. This suggests that they are not appropriate for factor analysis (FA) (Coakes, 2007). EFA should not be used if the correlation matrix is an identity matrix (i.e., there is no relationship between the items) (Kraiser, 1970).

Table 6.56 Correlations Matrix for Employees IT Knowledge

		EK1	EK 2	EK 3	EK 4	EK 5
Correlations	EK1	1	.534**	.270**	.278**	.218**
	EK2	.534**	1	.367**	.212**	.217**
	EK3	.270**	.367**	1	.355**	.078
	EK4	.278**	.212**	.355**	1	.114*
	EK5	.218**	.217**	.078	.114*	1

**. Correlation is significant at the 0.01 level (2-tailed).
*. Correlation is significant at the 0.05 level (2-tailed).

KMO and Bartlett's Test for Employees IT Knowledge

As shown in Table 6.57, the results revealed that for KMO correlation items for the technology strategy is 0.665. The result above the minimum acceptable level of 0.60 (Coakes et al., 2006) Test of Bartlett's test of sphericity (chi-square = 264.209) was highly significant at $p< 0.000$. indicating adequate nature of relations between the variables. The data therefore appropriate.

Table 6. 57 KMO and Bartlett's Test for Employees IT Knowledge

KMO and Bartlett's Test		
Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.665
Bartlett's Test of Sphericity	Approx. Chi-Square	264.209

	df	10
	Sig.	.000

Factor Loading for employees IT Knowledge Scale

Factor Loading of scale items for employees IT knowledge was examined. Factor loading below 0.4 are considered low and low- items should be suppressed (Field, 2005). In this study, the recommended cut oof factor loading of 0.5 ensured that all variables had practical significant (Hair et al., 2006). As shown in Table 6.58, the loading values of all five items exceed the cut-off level of 0.50.

Table 6.58 Factor Loading for employees IT Knowledge Scale

Items	Component 1
EK1	.669
EK2	.754
EK3	.656
EK4	.576
EK5	.471

Extraction Method: Principal Component Analysis (PCA)

a. 1 component extracted.

Analysis for Technology Infrastructure Scale (TI)

The findings for correlation coefficients between items for the IT Infrastructure are provided in Table 6.59. The analysis of IT Infrastructure Scale is 0.122 to 1.000, and a positive correlation is calculated on a scale from 0.1 to 1.0. Week positive correlation would be in the range of 0.1 to 0.3. it appears that the technology infrastructure scale has weak positive correlation. According to Hair, Black, Babin, Anderson, and Tatham (2011), as well as Tabachnick and Fidell (2001), it is recommended to reconsider using FA if the correlations are less than 0.30 (Hair, Black, Babin, Anderson, & Tatham, 2011). EFA should not be used if the correlation matrix is an identity matrix (i.e., there is no relationship between the items) (Kraiser, 1970).

Table 6.59 Correlations Matrix for Technology Infrastructure

		TI 1	TI 2	TI 3	TI 4	TI 5
Correlations	**TI 1**	1	.364**	.280**	.187**	.210**
	TI 2	.364**	1	.345**	.137**	.127*
	TI 3	.280**	.345**	1	.327**	.122*
	TI 4	.187**	.137**	.327**	1	.149**
	TI 5	.210**	.127*	.122*	.149**	1

**. Correlation is significant at the 0.01 level (2-tailed).
*. Correlation is significant at the 0.05 level (2-tailed).

KMO and Bartlett's Test for Technology Infrastructure

As shown in Table 6.60, the results revealed that for KMO correlation items for the Technology strategy is 0.671. The result above the minimum acceptable level of 0.60 (Coakes et al., 2006) Test of Bartlett's test of sphericity (chi-square = 174.891) was highly significant at p< 0.000. indicating adequate nature of relations between the variables. The data therefore appropriate.

Table: 6. 60 KMO and Bartlett's Test for Technology Infrastructure

KMO and Bartlett's Test		
Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.671
Bartlett's Test of Sphericity	Approx. Chi-Square	174.891
	df	10
	Sig.	.000

Factor Loading for Technology Infrastructure Scale

Factor Loading of scale items for Technology Infrastructure was examined. Factor loading below 0.4 are considered low and low- items should be suppressed (Field, 2005). In this study, the recommended cut oof factor loading of 0.5 ensured that all variables had practical significant (Hair et al., 2006). As shown in Table 6.61, the loading values of all five items exceed the cut-off level of 0.50.

Table 6.61 Factor Loading for Technology Infrastructure Scale

Component Matrix

Items	**Component 1**
TI 1	.688
TI 2	.674
TI 3	.710
TI 4	.557
TI 5	.431

Extraction Method: Principal Component Analysis (PCA)
a. 1 components extracted.

Analysis for Managerial Support Scale (MS)

The findings for correlation coefficients between items for the managerial support are provided in Table 6.62. The analysis of managerial support Scale is 0.089 to 1.000, and positive correlation is calculated on a scale from 0.1 to 1.0. Week positive correlation would be in the range of 0.1 to 0.3. it appears that managerial support scale has week positive correlation. It would seem that a modest positive correlation would fall between 0.1 and 0.3. According to Hair, Black, Babin, Anderson, and Tatham (2011) recommended to reconsider using FA if the correlations are less than 0.30 (Tabachnick & Fidell (2001). This suggests that they are not appropriate for factor analysis (FA) (Coakes, 2005).

Table 6.62 Correlations Matrix for Managerial Support

		MS 1	**MS2**	**MS3**	**MS4**	**MS5**
Correlations	**MS1**	1	.393**	.227**	.267**	.267**
	MS2	.393**	1	.348**	.164**	.152**
	MS3	.227**	.348**	1	.298**	.089
	MS4	.267**	.164**	.298**	1	.288**
	MS5	.267**	.152**	.089	.288**	1

**. Correlation is significant at the 0.01 level (2-tailed).
*. Correlation is significant at the 0.05 level (2-tailed).

KMO and Bartlett's Test for Managerial Support

As shown in Table 6.63, the results revealed that for KMO correlation items for the Managerial Support is .657. The result above the minimum acceptable level of 0.60 (Coakes et al., 2006)

Test of Bartlett's test of sphericity (chi-square = 209.615) was highly significant at p< 0.000. indicating adequate nature of relations between the variables. The data therefore appropriate.

Table: 6. 63 KMO and Bartlett's Test for Managerial Support

KMO and Bartlett's Test		
Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.657
Bartlett's Test of Sphericity	Approx. Chi-Square	209.615
	df	10
	Sig.	.000

Factor Loading for Managerial Support Scale

Factor Loading of scale items for Managerial Support was examined. Factor loading below 0.4 are considered low and low- items should be suppressed (Field, 2005). In this study, the recommended cut oof factor loading of 0.5 ensured that all variables had practical significant (Hair et al., 2006). As shown in Table 6.64, the loading values of all five items exceed the cut-off level of 0.50.

Table 6.64 Factor Loading for Managerial Support Scale

Component Matrix

Items	**Component 1**
MS1	.706
MS2	.671
MS3	.623
MS4	.630
MS5	.523

Extraction Method: Principal Component Analysis (PCA)
a. 1 components extracted.

Analysis for Training Scale (TR)

As Table 6.65 shows, the analysis correlation coefficients of managerial support Scale is 0.155 to 1.000, and positive correlation is calculated on a scale from 0.1 to 1.0. It would seem that a modest positive correlation would fall between 0.1 and 0.3. Week positive correlation would be in the range of 0.1 to 0.3. it appears that training scale has week positive correlation. According to Hair, Black, Babin, Anderson, and Tatham (2011) recommended to reconsider using FA if the correlations are less than 0.30 (Tabachnick & Fidell (2001). This suggests that they are not appropriate for factor analysis (FA) (Coakes, 2005).

Table 6.65 Correlations Matrix for Training

		TR1	TR2	TR3	TR4	TR5
Correlations	**TR1**	1	.340**	.158**	.164**	.199**
	TR2	.340**	1	.320**	.112*	.155**
	TR3	.158**	.320**	1	.312**	.203**
	TR4	.164**	.112*	.312**	1	.315**
	TR5	.199**	.155**	.203**	.315**	1

**. Correlation is significant at the 0.01 level (2-tailed).
*. Correlation is significant at the 0.05 level (2-tailed).

KMO and Bartlett's Test for Training

As shown in Table 6.66, the results revealed that for KMO correlation items for the Training is 0.637. The result above the minimum acceptable level of 0.60 (Coakes et al., 2006). Test of Bartlett's test of sphericity (chi-square = 178.264) was highly significant at $p< 0.000$. indicating adequate nature of relations between the variables. The data therefore appropriate.

Table: 6. 66 KMO and Bartlett's Test for Training

KMO and Bartlett's Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.637
Bartlett's Test of Sphericity	Approx. Chi-Square	178.264
	df	10
	Sig.	.000

Factor Loading for Training Scale

Factor Loading of scale items for training was examined. Factor loading below 0.4 are considered low and low- items should be suppressed (Field, 2005). In this study, the recommended cut oof factor loading of 0.5 ensured that all variables had practical significant (Hair et al., 2006). As shown in Table 6.67, the loading values of all five items exceed the cut-off level of 0.50.

Table 6.67 Factor Loading for Training Scale

Component Matrix

Items	**Component 1**
TR1	.589
TR2	.628
TR3	.664
TR4	.614
TR5	.595

Extraction Method: Principal Component Analysis (PCA)
a. 1 components extracted.

Analysis for Reward System Scale (RS)

As Table 6.68 shows, the analysis correlation coefficients of managerial support scale is 0.162 to 1.000, and positive correlation is calculated on a scale from 0.1 to 1.0. It would seem that a modest positive correlation would fall between 0.1 and 0.3. Week positive correlation would be in the range of 0.1 to 0.3. it appears that Reward System Scale has week positive correlation According to Hair, Black, Babin, Anderson, and Tatham (2011) recommended to reconsider using FA if the correlations are less than 0.30 (Tabachnick & Fidell (2001). This suggests that they are not appropriate for factor analysis (FA) (Coakes, 2005).

Table 6.68 Correlations Matrix for Reward System

		RS1	**RS 2**	**RS 3**	**RS 4**	**RS 5**
Correlations	**RS 1**	1	.159**	.190**	.387**	.187**
	RS 2	.159**	1	.254**	.139**	.137**
	RS 3	.190**	.254**	1	.363**	.162**
	RS 4	.387**	.139**	.363**	1	.348**
	RS 5	.187**	.137**	.162**	.348**	1

**. Correlation is significant at the 0.01 level (2-tailed).
*. Correlation is significant at the 0.05 level (2-tailed).

KMO and Bartlett's Test for Reward System

As shown in Table 6.69, the results revealed that for KMO correlation items for the Reward System is 0.656. The result above the minimum acceptable level of 0.60 (Coakes et al., 2006). Test of Bartlett's test of sphericity (chi-square = 190.297) was highly significant at p< 0.000. indicating adequate nature of relations between the variables. The data therefore appropriate.

Table: 6.69 KMO and Bartlett's Test for Reward System

KMO and Bartlett's Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.656
Bartlett's Test of Sphericity	Approx. Chi-Square	190.297
	df	10
	Sig.	.000

Factor Loading for Reward System Scale

Factor Loading of scale items for Reward System was examined. Factor loading below 0.4 are considered low and low- items should be suppressed (Field, 2005). In this study, the recommended cut oof factor loading of 0.5 ensured that all variables had practical significant (Hair et al., 2006). As shown in Table 6.70, the loading values of all five items exceed the cut-off level of 0.50.

Table 6.70 Factor Loading for Reward System Scale

Component Matrix

Items	Component 1
RS 1	.630
RS 2	.469
RS 3	.639
RS 4	.774
RS 5	.579

Extraction Method: Principal Component Analysis (PCA)
a. 1 components extracted.

Analysis for Government Support Scale (GS)

The findings for correlation coefficients between items for the government support are provided in Table 6.71. The analysis of government support scale is 0.359 to 1.000, and positive correlation is calculated on a scale from 0.1 to 1.0. A moderate positive correlation would be between 0.3 and 0.5. It appears that Government Support Scale has A moderate positive correlation. The correlation loadings were categorized by Taherdoost, Sahibuddin, and Jalaliyoon (2022) as 0.30 = little, 0.40 = considerable, and 0.50 = practically. This suggests that they are appropriate for factor analysis (FA) (Coakes, 2005). EFA should be used if the correlation matrix is an identity matrix (i.e., there is no relationship between the items) (Kraiser, 1970).

Table 6.71 Correlations Matrix for Government Support

		GS1	**GS2**	**GS3**	**GS4**	**GS5**
Correlations	**GS1**	1	.390**	.225**	.351**	.359**
	GS2	.390**	1	.448**	.336**	.460**
	GS3	.225**	.448**	1	.449**	.456**
	GS4	.351**	.336**	.449**	1	.444**
	GS5	.359**	.460**	.456**	.444**	1

**. Correlation is significant at the 0.01 level (2-tailed).
*. Correlation is significant at the 0.05 level (2-tailed).

KMO and Bartlett's Test for Government Support

As shown in Table 6.72, the results revealed that for KMO correlation items for the Government Support is 0.780. The result above the minimum acceptable level of 0.60 (Coakes et al., 2006). Test of Bartlett's test of sphericity (chi-square = 414.372) was highly significant at $p< 0.000$. indicating adequate nature of relations between the variables. The data therefore appropriate.

Table: 6. 72 KMO and Bartlett's Test for Government Support

KMO and Bartlett's Test	
Kaiser-Meyer-Olkin Measure of Sampling Adequacy.	.780

Bartlett's Test of Sphericity	Approx. Chi-Square	414.372
	df	10
	Sig.	.000

Factor Loading for Government Support Scale

Factor Loading of scale items for Reward System was examined. Factor loading below 0.4 are considered low and low- items should be suppressed (Field, 2005). In this study, the recommended cut oof factor loading of 0.5 ensured that all variables had practical significant (Hair et al., 2006). As shown in Table 6.73, the loading values of all five items exceed the cut-off level of 0.50.

Table 6.73 Factor Loading for Government Support Scale

Component Matrix

Items	**Component 1**
GS1	.623
GS2	.739
GS3	.727
GS4	.720
GS5	.771

Extraction Method: Principal Component Analysis (PCA)
a. 1 components extracted.

Analysis for Government Regulation Scale (GR)

The findings for correlation coefficients between items for the government regulation are provided in Table 6.74. The analysis of government support scale is 0. 306 to 1.000, and positive correlation is calculated on a scale from 0.1 to 1.0. A moderate positive correlation would be between 0.3 and 0.5. It appears that Government Regulation Support Scale has A moderate positive correlation. The correlation loadings were categorized as 0.30 = little, 0.40 = considerable, and 0.50 = practically (Taherdoost, Sahibuddin, and Jalaliyoon, 2022). This suggests that they are appropriate for factor analysis (FA) (Coakes, 2005). EFA should be used if the correlation matrix is an identity matrix (i.e., there is no relationship between the items) (Kraiser, 1970).

Table 6.74 Correlations Matrix for Government Regulation

		GR1	GR2	GR3	GR4	GR5
Correlations	**GR1**	1	.392**	.232**	.240**	.335**
	GR2	.392**	1	.376**	.354**	.330**
	GR3	.232**	.376**	1	.512**	.306**
	GR4	.240**	.354**	.512**	1	.475**
	GR5	.335**	.330**	.306**	.475**	1

**. Correlation is significant at the 0.01 level (2-tailed).
*. Correlation is significant at the 0.05 level (2-tailed).

KMO and Bartlett's Test for Government Regulation

As shown in Table 6.75, the results revealed that for KMO correlation items for the Government Regulationis 0.738. The result above the minimum acceptable level of 0.60 (Coakes et al., 2006). Test of Bartlett's test of sphericity (chi-square = 368.478) was highly significant at p< 0.000. indicating adequate nature of relations between the variables. The data therefore appropriate.

Table: 6.75 KMO and Bartlett's Test for Government Regulation

KMO and Bartlett's Test		
Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.738
Bartlett's Test of Sphericity	Approx. Chi-Square	368.478
	df	10
	Sig.	.000

Factor Loading for Government Regulation Scale

Factor Loading of scale items for Government Regulation was examined. Factor loading below 0.4 are considered low and low- items should be suppressed (Field, 2005). In this study, the recommended cut oof factor loading of 0.5 ensured that all variables had practical significant (Hair et al., 2006). As shown in Table 6.76 the loading values of all five items exceed the cut-off level of 0.50.

Table 6.76 Factor Loading for Government Regulation Scale

Component Matrix

Items	Component 1
GR1	.600
GR2	.702
GR3	.706
GR4	.762
GR5	.706

Extraction Method: Principal Component Analysis (PCA)
a. 1 components extracted.

Analysis for Competitive Pressure Scale (CP)

The findings for correlation coefficients between items for the government support are provided in Table 6.77. The analysis of government support scale is 0. 240 to 1.000, and positive correlation is calculated on a scale from 0.1 to 1.0. week positive correlation would be between 0.1 to 0.3. It appears that Competitive Pressure Scale has week positive correlation. It would seem that a modest positive correlation would fall between 0.1 and 0.3. The correlation loadings were categorized by Taherdoost, Sahibuddin, and Jalaliyoon (2022) as 0.30 = little, 0.40 = considerable, and 0.50 = practically. This suggests that they are not appropriate for factor analysis (FA) (Coakes, 2005). EFA should be not used if the correlation matrix is an identity matrix (i.e., there is no relationship between the items) (Kraiser, 1970).

Table 6.77 Correlations Matrix for Competitive Pressure

		CP1	CP2	CP3	CP4	CP5
Correlations	**CP1**	1	.421**	.270**	.242**	.298**
	CP2	.421**	1	.295**	.195**	.240**
	CP3	.270**	.295**	1	.142**	.287**
	CP4	.242**	.195**	.142**	1	.274**
	CP5	.298**	.240**	.287**	.274**	1

**. Correlation is significant at the 0.01 level (2-tailed).
*. Correlation is significant at the 0.05 level (2-tailed).

KMO and Bartlett's Test for Competitive Pressure

As shown in Table 6.78, the results revealed that for KMO correlation items for the Competitive Pressure is 0.724. The result above the minimum acceptable level of 0.60 (Coakes et al., 2006). Test of Bartlett's test of sphericity (chi-square = 210.365) was highly significant at p< 0.000. indicating adequate nature of relations between the variables. The data therefore appropriate.

Table: 6.78 KMO and Bartlett's Test for Competitive Pressure

KMO and Bartlett's Test		
Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.724
Bartlett's Test of Sphericity	Approx. Chi-Square	210.365
	df	10
	Sig.	.000

Factor Loading for Competitive Pressure Scale

Factor Loading of scale items for Competitive Pressure was examined. Factor loading below 0.4 are considered low and low- items should be suppressed (Field, 2005). In this study, the recommended cut oof factor loading of 0.5 ensured that all variables had practical significant (Hair et al., 2006). As shown in Table 6.79 the loading values of all five items exceed the cut-off level of 0.50.

Table 6.79 Factor Loading for Competitive Pressure Scale

Component Matrix

Items	**Component 1**
CP1	.722
CP2	.690
CP3	.612
CP4	.532
CP5	.651

Extraction Method: Principal Component Analysis (PCA)
a. 1 components extracted.

Analysis for Peer Support Scale (PS)

The findings for correlation coefficients between items for the peer support are provided in Table 6.80. The analysis of peer support scale is 0.290 to 1.000, and positive correlation is calculated on a scale from 0.1 to 1.0. The correlation loadings were categorized as 0.30 = little, 0.40 = considerable, and 0.50 = practically (Taherdoost, Sahibuddin, and Jalaliyoon, 2022). This suggests that they are appropriate for factor analysis (FA) (Coakes, 2005). EFA should be used if the correlation matrix is an identity matrix (i.e., there is no relationship between the items) (Kraiser, 1970).

Table 6.80 Correlations Matrix for Peer Support

		PS1	PS2	PS3	PS4	PS5
Correlations	**PS1**	1	.327**	.329**	.393**	.290**
	PS2	.327**	1	.527**	.432**	.400**
	PS3	.329**	.527**	1	.454**	.408**
	PS4	.393**	.432**	.454**	1	.454**
	PS5	.290**	.400**	.408**	.454**	1

**. Correlation is significant at the 0.01 level (2-tailed).
*. Correlation is significant at the 0.05 level (2-tailed).

KMO and Bartlett's Test for Peer Support

As shown in Table 6.81, the results revealed that for KMO correlation items for the Competitive Pressure is 0.809. The result above the minimum acceptable level of 0.60 (Coakes et al., 2006). Test of Bartlett's test of sphericity (chi-square = 423.629) was highly significant at p< 0.000. indicating adequate nature of relations between the variables. The data therefore appropriate

Table: 6.81 KMO and Bartlett's Test for Peer Support

KMO and Bartlett's Test		
Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		0.809
Bartlett's Test of Sphericity	Approx. Chi-Square	423.629
	df	10
	Sig.	.000

Factor Loading for Peer Support Scale

Factor Loading of scale items for Peer Support was examined. Factor loading below 0.4 are considered low and low- items should be suppressed (Field, 2005). In this study, the recommended cut oof factor loading of 0.5 ensured that all variables had practical significant (Hair et al., 2006). As shown in Table 6.82 the loading values of all five items exceed the cut-off level of 0.50.

Table 6.82 Factor Loading for Peer Support Scale

Component Matrix

Items	**Component 1**
PS1	.620
PS2	.753
PS3	.764
PS4	.765
PS5	.705

Extraction Method: Principal Component Analysis (PCA)

a. 1 component extracted.

Analysis for Social Network Scale (SN)

As Table 6.83 shows, the analysis correlation coefficients of managerial support scale are 0. 279 to 1.000, and positive correlation is calculated on a scale from 0.1 to 1.0. It would seem that a modest positive correlation would fall between 0.1 and 0.3. According to Hair, Black, Babin, Anderson, and Tatham (2011) recommended to reconsider using FA if the correlations are less than 0.30 (Tabachnick & Fidell (2001). This suggests that they are not appropriate for factor analysis (FA) (Coakes, 2005).

Table 6.83 Correlations matrix for Social Network

		NS1	**NS2**	**SN3**	**NS4**	**NS5**
Correlations	**NS1**	1	.421**	.135*	.124*	.296**
	NS2	.421**	1	.257**	.137**	.297**
	NS3	.135*	.257**	1	.353**	.279**
	NS4	.124*	.137**	.353**	1	.441**
	NS5	.296**	.297**	.279**	.441**	1

**. Correlation is significant at the 0.01 level (2-tailed).
*. Correlation is significant at the 0.05 level (2-tailed).

KMO and Bartlett's Test for Social Network

As shown in Table 6.84, the results revealed that for KMO correlation items for the Social Network is 0.660. The result above the minimum acceptable level of 0.60 (Coakes et al., 2006). Test of Bartlett's test of sphericity (chi-square = 265.498) was highly significant at p< 0.000. indicating adequate nature of relations between the variables. The data therefore appropriate.

Table: 6.84 KMO and Bartlett's Test for Social Network

KMO and Bartlett's Test		
Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.660
Bartlett's Test of Sphericity	Approx. Chi-Square	265.498
	df	10
	Sig.	.000

Factor Loading for Social Network Scale

Factor Loading of scale items for Social Network was examined. Factor loading below 0.4 are considered low and low- items should be suppressed (Field, 2005). In this study, the recommended cut oof factor loading of 0.5 ensured that all variables had practical significant (Hair et al., 2006). As shown in Table 6.85 the loading values of all five items exceed the cut-off level of 0.50.

Table 6.85 Factor Loading for Social Network Scale

Component Matrix

Items	**Component 1**
NS1	.592
NS2	.646
NS3	.614
NS4	.639
NS5	.743

Extraction Method: Principal Component Analysis (PCA)

a. 1 component extracted.

Analysis for Religious Beliefs Scale (RB)

The findings for correlation coefficients between items for the Religious Beliefsare provided in Table 6.86. The analysis of Religious Beliefsscale is 0. 353 to 1.000, and positive correlation is calculated on a scale from 0.1 to 1.0. It would seem that a modest positive correlation would fall between 0.1 and 0.3. The correlation loadings were categorized by Taherdoost, Sahibuddin, and Jalaliyoon (2022) as 0.30 = little, 0.40 = considerable, and 0.50 = practically. This suggests that they are appropriate for factor analysis (FA) (Coakes, 2007). EFA should be used if the correlation matrix is an identity matrix (i.e., there is no relationship between the items) (Kraiser, 1970).

Table 6.86 Correlations matrix for Religious Beliefs

		RB1	RB 2	RB 3	RB 4	RB 5
Correlations	RB 1	1	.513**	.362**	.274**	.353**
	RB 2	.513**	1	.424**	.383**	.400**
	RB 3	.362**	.424**	1	.548**	.455**
	RB 4	.274**	.383**	.548**	1	.517**
	RB 5	.353**	.400**	.455**	.517**	1

****. Correlation is significant at the 0.01 level (2-tailed).**
***. Correlation is significant at the 0.05 level (2-tailed).**

The correlation matrix for eight analyses appears not to be an identity matrix. It would seem that a modest positive correlation would fall between 0.1 and 0.3. Researchers can proceed with the Exploratory Factor Analyses (EFA) if the KMO suggests sample adequacy and Bartlett's test of sphericity reveals the item correlation matrix is not an identity matrix (Netemeyer, Bearden & Sharma, 2003; Taherdoost, Sahibuddin, & Jalaliyoon, 2022).

KMO and Bartlett's Test for Religious Beliefs

As shown in Table 6.87, the results revealed that for KMO correlation items for the Religious Beliefs is 0.782. The result above the minimum acceptable level of 0.60 (Coakes et al., 2006). Test of Bartlett's test of sphericity (chi-square = 493.646) was highly significant at p< 0.000. indicating adequate nature of relations between the variables. The data therefore appropriate**.**

Table: 6. 87 KMO and Bartlett's Test for Religious Beliefs

KMO and Bartlett's Test		
Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.782
Bartlett's Test of Sphericity	Approx. Chi-Square	493.646
	df	10
	Sig.	.000

Factor Loading for Religious Beliefs Scale

Factor Loading of scale items for Religious Beliefs was examined. Factor loading below 0.4 are considered low and low- items should be suppressed (Field, 2005). In this study, the recommended cut oof factor loading of 0.5 ensured that all variables had practical significant (Hair et al., 2006). As shown in Table 6.88 the loading values of all five items exceed the cut-off level of 0.50.

Table 6.88 Factor Loading for Religious Beliefs Scale

Component Matrix

Items	Component 1
RB 1	.664
RB 2	.738
RB 3	.769
RB 4	.750
RB 5	.747

Extraction Method: Principal Component Analysis (PCA)

a. 1 component extracted.

The results revealed that KMO correlation items for all 12 independent variables above the minimum acceptable level of 0.60 are considered adequate for analysis of the EFA output (Netemeyer, Bearden & Sharma, 2003; Taherdoost, Sahibuddin, and Jalaliyoon (2022).

6.11 Analysis effect of demographics on perception to using AI applications

The regression model summary as shown below in Table 6.89. The results display that r-square (R^2) is the correlation coefficient squared (R^2=0.635), which is also known as the coefficient of determination. The R^2 value indicates the percentage of total variation of Y (dependent variables) that is explained by the independent variables. The standard error of the estimation is another measure of the predictions' accuracy, which represents an estimate of the standard deviation of the actual dependent values about the regression line. Furthermore, results of Durbin-Watson statistics inform us that there is no problem regarding autocorrelation. As a rule of thumb, values of less than 1 or greater than 3 are cause for concern (Field, 2005, p. 189). For this study's data, the value is (1.96859), so the assumption has been met.

Table 6.89 Regression Model Summary

Model	R	R Square	Adjusted R Square	Durbin-Watson
1	.797a	.635	.627	1.96859

a. Predictors: (Constant), Role, Industry, Qualifications, Gender, Experience, Age, Employees
b. Dependent Variable: perceptions

The results of an analysis of variance (ANOVA) in Table 6.90 indicate whether the model successfully predicted demographics. F-test in ANOVA reflects the contribution to prediction accuracy as a result of model fitting relative to any potential model imperfection. According to the analysis, the model significantly outperforms the intercept alone in predicting the dependent variables: F-ration = 88.308, $p<0.001$. The research leads to the conclusion that the model significantly ($p<0.001$.) outperforms the control group in predicting the dependent variables.

Table 6.90 Analysis of variance (ANOVA)

Model	Sum of Squares	Df	Mean Square	F	Sig.
Regression	2395.562	7	342.223	88.308	.000
Residual	1379.625	356	3.875		
Total	3775.187	363			

a. Dependent Variable: perceptions

b. Predictors: (Constant), Role, Industry, Qualifications, Gender, Experience, Age, Employees

Table 6.91 below presents the results on the effect of demographics variables (Gender, Age, Qualifications, Experience, Industry, Employees and Role). Regarding the owners/managers perception to using the AI in SMEs in Amman the capital of Jordan. The results show that, Age, Qualifications, Experience, Employees and Role significant effect on perception while the gender and industry variables not significant effect on perception to use and adopt the digital technologies such AI.

Table 6.91: Results of regression of demographics and perception as dependent variable

		Unstandardized Coefficients		Standardized Coefficients		
		B	Std. Error	Beta	t	Sig.
1	(Constant)	3.850	.739		5.213	.000
	Gender	.166	.235	.024	.707	.480
	Age	.486	.082	.202	5.959	.000
	Qualifications	.301	.115	.084	2.615	.009
	Experience	1.496	.107	.470	13.979	.000
	Industry	.031	.036	.028	.877	.381
	Employees	1.305	.125	.373	10.406	.000
	Role	.239	.077	.109	3.111	.002

a. Dependent Variable: perceptions

6.11 Analysis of Perception Scale (PR)

Correlations Matrix for Perception

The findings for correlation coefficients between items for the Perception Beliefs are provided in Table 6.92. The analysis of Perception scale is 0.173** to 1.000, and positive correlation is calculated on a scale from 0.1 to 1.0. A modest positive correlation would fall between 0.1 and 0.3. The correlation loadings were categorized by Taherdoost, Sahibuddin, and Jalaliyoon (2022) as 0.30 = little, 0.40 = considerable, and 0.50 = practically. This suggests that they are appropriate for factor analysis (FA) (Coakes, 2007). EFA should be used if the correlation matrix is an identity matrix (i.e., there is no relationship between the items) (Kraiser, 1970).

Table 6.92 Correlations Matrix for Perception

		PR 1	PR 1	PR 1	PR 1	PR 1
Correlations	**PR 1**	1.000	.213**	.083	.131**	.204**
	PR 2	.213**	1.000	.218**	.152**	.173**
	PR 3	.083	.218**	1.000	.317**	.219**
	PR 4	.083	.218**	1.000	.317**	.219**
	PR 5	.204**	.173**	.219**	.369**	1.000

**. Correlation is significant at the 0.01 level (2-tailed).
*. Correlation is significant at the 0.05 level (2-tailed).

KMO and Bartlett's Test for perception

As shown in Table 6.93, the results revealed that for KMO correlation items for the perception is 0.688. The result above the minimum acceptable level of 0.60 (Coakes et al., 2006). Test of Bartlett's test of sphericity (chi-square = 238.338) was significant at $p< 0.000$. indicating adequate nature of relations between the variables. The data therefore appropriate**.**

Table: 6. 93 KMO and Bartlett's Test for perception

KMO and Bartlett's Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.688
Bartlett's Test of Sphericity	Approx. Chi-Square	238.338
	Df	10
	Sig.	.000

Factor Loading for Perception Scale

Factor Loading of scale items for Perception was examined. Factor loading below 0.4 are considered low and low- items should be suppressed (Field, 2005). In this study, the recommended cut oof factor loading of 0.5 ensured that all variables had practical significant (Hair et al., 2006). As shown in Table 6.94 the loading values of all five items exceed the cut-off level of 0.50.

Table 6.94 Factor Loading for Perception Scale

Component Matrix

Items	Component 1
PR 1	.490
PR 2	.593
PR 3	.671
PR 4	.730
PR 5	.716

Extraction Method: Principal Component Analysis (PCA)

a. 1 component extracted.

6.12 Multicollinearity Test

Collinearity denotes a high correlation between the independent variables and lowers the model's accuracy, and it is a problem that often appears in the analysis of regression models (Craney & Surles, 2002). It is the condition where one independent variable is a linear function of another independent variable. Variance inflation factor (VIF) measures the strength of the correlation between the independent variables in regression analysis. Two valuable and helpful indicators for carrying out a multicollinearity test between variables are tolerance and VIF (Arabameri, Pradhan, Rezaei & Sohrabi, 2020). The reciprocal of variance inflation is tolerance. For detecting collinearity in multiple regression, the VIF and tolerance statistics are closely related (Miles, 2014). As long as the tolerance values are less than 0.10 and the VIF values are more extensive than 10, the assumption of multicollinearity is not violated (Hair, Anderson, Tatham & Black, 1996; Arabameri, Pradhan, Rezaei & Sohrabi, 2020). High multicollinearity is problematic because it weakens the statistical significance of independent variables (Allen, 2004). Table 6.95 displays the collinearity statistics below.

Table: 6. 95 Collinearity Statistics

Collinearity		
Variables	**Tolerance**	**VIF**
strategy	.762	1.312
knowledge	.719	1.391

infrastructure	.888	1.126
Managerial support	.705	1.419
Training	.777	1.286
Reward system	.717	1.395
Government support	.695	1.438
Government regulations	.522	1.917
Competitive pressure	.526	1.900
peers ‘supports	.731	1.368
Social network	.752	1.330
Religious beliefs	.706	1.417

6.14 Regression Analysis

In empirical investigations, regression is the most often employed statistical methodology across various disciplines, from the social and economic sciences to the biological sciences. Strong correlations between predictors are a scenario that is present in the majority of regression applications. In order to create an equation based on the relationship between the response and predictor variables, regression analysis is a statistical technique (Hosseini, Mousavi & Monjezi, 2022). Theories usually contend that numerous variables influence a dependent variable at the same time. Multiple linear regression analysis is a technique for assessing the effects of various factors simultaneously. The application of multiple regression analysis is acceptable in a variety of situations. For example, it has been used in economics to predict how changes in pricing and income will affect gasoline demand; the possibility that an unemployed person will double up (share housing arrangements with family or friends) are influenced by various variables, including the person's age and educational attainment (Sjoquist, Schroeder, & Stephan, 2016). The model developed for this research to improve theoretical foundations and to promote management awareness of, understanding of and support for digital technologies adoption in the Jordanian SMEs.

A multiple regression analysis provided an objective means of assessing the predictive power of a set of independent variables included in the conceptual model. Each independent variable was weighted by the regression analysis to ensure maximum prediction from the set of independent variables. The weights denote the relative contribution of the independent variables and facilitate interpretations that influence each variable in the research model. In this research, the following 12 variables were classified as independent variables: strategy, knowledge, infrastructure, managerial support, training, Reward system, government support, government regulations, competitive pressure, peers 'supports, social network and religious beliefs. The sample of 364 observations meets the proposed guideline for the ratio of observations to independent variables as stated by Hair et al. (1998, p.166). This sample confirms that there will be no danger of over-fitting the results, and does in fact validate the outcomes, thus ensuring the findings' generalizability. The sample is considered adequate and the assumptions for the individual variables are met when the regression analysis is defined in terms of dependent and independent variables. The overall model fit was evaluated, followed by an estimation of the regression model.

The results of the study are shown in Table 6.96. The results display that r-square (R^2) is the correlation coefficient squared (R^2=.544), which is also known as the coefficient of determination. The R^2 value indicates the percentage of total variation of Y (dependent variables) that is explained by the independent variables. In this analysis, .529% of the variation in people's acceptance and use of AI can be explained by strategy, knowledge, infrastructure, managerial support, training, reward system, government support, government regulations, competitive pressure, peers 'supports, social network and religious beliefs. Prior research recommends that an R^2 of .15 indicates moderate variance and an R^2 of .35 indicates a great amount of variance (Cohen, 2013; Talukder, AlSheddi, Sharma & Islam, 2022). The standard error of the estimation is another measure of the predictions' accuracy, which represents an estimate of the standard deviation of the actual dependent values about the regression line. Furthermore, results of Durbin-Watson statistics inform us that there is no problem regarding autocorrelation. As a rule of thumb, values of less than 1 or greater than 3 are definitely cause for concern (Field, 2005, p. 189). For this study's data, the value is 1.607, so the assumption has been met. Table 6.96 summarizes the model.

Table 6.96 Regression Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson	Model
1	.738a	.544	.529	2.21377	1.607	1

a. Predictors: (Constant), Religious beliefs, peers 'supports, infrastructure, Competitive pressure, knowledge, strategy, Training, Reward system, social network, Managerial support, Government support, Government regulations
b. Dependent Variable: perceptions

The results of an analysis of variance (ANOVA) in Table 6.97 indicate whether the model successfully predicted the outcome. F-test in ANOVA reflects the contribution to prediction accuracy as a result of model fitting relative to any potential model imperfection. According to the analysis, the model significantly outperforms the intercept alone in predicting the dependent variables: F-ration = 34.943, $p<0.\ 001$. The research leads to the conclusion that the model significantly ($p<0.001$.) outperforms the control group in predicting the dependent variables.

Table 6. 97 Analysis of variance (ANOVA)

Model	Sum of Squares	Df	Mean Square	F	Sig.
Regression	2055.008	12	171.251	34.943	.000
Residual	1720.179	351	4.901		
Total	3775.187	363			

a. Predictors: (Constant), Religious beliefs, peers ‘supports, infrastructure, Competitive pressure, knowledge, strategy, Training, Reward system, social network, Managerial support, Government support, Government regulations.
b. Dependent Variable: perceptions.

In Table 6.98 below shows that eight out of twelve variables had significant effect on perception to the adoption of digital technologies. The unstandardized coefficient B-values represent the relationship between digital technologies perception and each predicting variable. If the B-value is positive, then it can be said that there is a positive relationship between the independent and dependent variables. For this data, eight significant predictors have positive B-values, thus indicating positive relationships, and four have negative B-values, indicating negative relationships. As strategy, government regulations, competitive pressure, and peers ‘supports to adopted and use digital technologies.

Table 6.98: Results of regression analysis with perception as dependent variable

		Unstandardized Coefficients		Standardized Coefficients		
		B	Std. Error	Beta	t	Sig.
1	(Constant)	-9.580	1.655		-5.788	.000
	strategy	.056	.043	.054	1.314	.190
	knowledge	.115	.046	.108	2.535	.012
	infrastructure	.091	.042	.083	2.171	.031
	Managerial support	.398	.045	.378	8.800	.000
	Training	.162	.043	.152	3.721	.000
	Reward system	.115	.045	.108	2.537	.012
	Government support	.115	.043	.116	2.680	.008
	Government regulations	.039	.054	.036	.725	.469
	Competitive pressure	.081	.058	.070	1.401	.162
	peers ‘supports	.060	.039	.064	1.527	.128
	Social network	.100	.042	.099	2.389	.017
	Religious beliefs	.120	.040	.127	2.957	.003

a. Dependent Variable: perceptions

6.15 Inter-correlations Among Study Variables

The study looked at the connections between two or more model variables. Investigating whether there is any direct evidence for links between the variables is the goal of this investigation. The outcomes will then serve as the foundation for other research, such as regression. Table 6.99 displays the correlation analysis for all research variables. The variables' Pearson's correlation coefficients (r) were significant at 0.01. In addition, the analysis's correlation matrix table demonstrates that the dependent and independent variables significantly correlate positively. Watson and colleagues (1988) found relatively weak correlations between positive and negative impact scales scores, ranging from –0.12 to –0.23. The optimal desired range (0.15 – 0.50) indicates internal consistency and unidimensionality (Sheppard & Mills, 2002).

Table 6.99 also shows that perception is significantly and positively related to three technological contexts: technology strategy (r=.367, p<.01), employees IT knowledge1 (r=.397, p<.01) and technology infrastructure (r=.230, p<.01). It is evident that level of perception is significantly and positively related to three organization contexts: managerial support (r=.598, p<.01), training (r=.386, p<.01) and reward system (r=.423, p<.01).

Perception is also significantly and positively related to three political- environmental context: Government support (r=.236, p<.01), Competitive pressure (r=.209, p<.01), -Customer pressure (r=.225, p<.01). The data also shows that perception is significantly and positively related to three socio-cultural: peer support (r=.202**, p<.01), Social network (r=.255, p<.01), and -Religious beliefs (r=.342, p<.01).

Table 6.99: Inter-correlations among study variables

Variables	**ST**	**KN**	**TF**	**MS**	**TR**	**RS**	**GS**	**GR**	**CP**	**PS**	**SN**	**RB**	RE
ST	1	.279**	.193**	.320**	.343**	.286**	.160**	.176**	.162**	.157**	.068	.077	.367**
KN	.279**	1	.133*	.280**	.328**	.356**	.336**	.060	.086	.201**	.012	.063	.397**
TF	193**	.133*	1	.107*	.196**	.231**	-.007	.014	.031	-.024	.060	.163**	.230**
MS	320**	.280**	.107*	1	.233**	.421**	.054	.185**	.186**	.047	.182**	.285**	.598**
TR	343**	.328**	.196**	.233**	1	.198**	.220**	.130*	.130*	.177**	-.019	.045	.386**
RS	.286**	.356**	.231**	.421**	.198**	1	.094	.032	.052	.083	.076	.195**	.423**
GS	.160**	.336**	-.007	.054	.220**	.094	1	-.083	-.100	.465**	-.024	-.049	.236**
GR	.176**	.060	.014	.185**	.130*	.032	-.083	1	.679**	-.092	.083	.181**	.209**
CP	162**	.086	.031	.186**	.130*	.052	-.100	.679**	1	-.044	.070	.177**	.225**
PS	157**	.201**	-.024	.047	.177**	.083	.465**	-.092	-.044	1	.136**	-.042	.202**
SN	.068	.012	.060	.182**	-.019	.076	-.024	.083	.070	.136**	1	.454**	.255**
RB	.077	.063	.163**	.285**	.045	.195**	-.049	.181**	.177**	-.042	.454**	1	.342**
RE	.367**	.397**	.230**	.598**	.386**	.423**	.236**	.209**	.225**	.202**	.255**	.342**	1

****. Correlation is significant at the 0.01 level (2-tailed).**
***. Correlation is significant at the 0.05 level (2-tailed).**

Table 6.100 shows that correlations among dependent and independent variables ranged from r=.254 to r=.636. This is corroborated by Hair et al. (1998), who stated that looking at the correlation matrix for the independent variables is the easiest and most obvious way to detect collinearity. The existence of high correlations (typically.90 and above) is the first sign of significant collinearity. Analysis was also conducted to detect the relationship between usage of AI and the outcomes. The results found that usage of AI is significantly and positively related to SMEs benefits: performance (r=.254, p<.01) and productivity (r=.254, p<.01). Usage is also positively and significantly related to SMEs profitability (r=.304, p<.01), enhanced customers satisfaction for SMEs (r=.398, p<.01), Market share (r=.254, p<.01) and better Sales improvement (r=.636, p<.01).

Table 6.100: Inter-correlations among usage and outcomes variables

Variables	PE	PR	PRO	CS	MS	SI	US
PE	1	.374**	.267**	.271**	.231**	.304**	.347**
PR	.374**	1	.524**	.302**	.239**	.398**	.327**
PRO	.267**	.524**	1	.311**	.368**	.357**	.268**
CS	.271**	.302**	.311**	1	.564**	.544**	.271**
MS	.231**	.239**	.368**	.564**	1	.636**	.269**
SI	.304**	.398**	.357**	.544**	.636**	1	.254**
US	.347**	.327**	.268**	.350**	.269**	.254**	1

**. Correlation is significant at the 0.01 level (2-tailed).
*. Correlation is significant at the 0.05 level (2-tailed).

The ideal range of average inter-item correlation is 0.15 to 0.50; less than this, and the items are not well correlated and do not measuring the same construct or idea very well (if at all). More than 0.50, and the items are so close as to be almost repetitive.

6.16 Analysis of Perception Effect on Usage

Based on Table 6.101 shows on the effect of perception about usage shows the correlation coefficient squared (R2=0.116) is the coefficient of determination. In this Analysis, only 11% of the variability. Result arising out of statistics approve there is no problem with autocorrelation. Durbin Watson's value is 2.046, greater than (1,440) and less than 2,559, it can be concluded that in this study there is no autocorrelation problem (Farida & Ardiansyah, 2022). So, the assumption has been met.

Table 6.101 Analysis Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
1	.341a	.116	.114	4.16132	2.046

a. Predictors: (Constant), perceptions
b. Dependent Variable: usage

Table: 6.102 above shows the outcome of the correlation indicates a highly significant relationship between the dependent variable (usage) and the independent variable (perception). The level of significance is 0.000. This finding agrees with the theory of reasoned action TRA (Fishbein & Ajzen, 1998; 1975) and the theory of planned behavior (TPB) (Ajzen, 1988, 2002), which assumes the full mediating role of perception on behavior. This outcome is slightly different from studies conducted using the technology acceptance model (Venkatesh & Davis, 2000; Davis et al., 1989). TRA and TPB insist that attitude completely mediates the relationships between beliefs and intentions (Dinev & Hu, 2007). These scholars found that an attitude toward using innovative technology is the most significant determinant of behavioral intention.

Table 6.102: Results of regression analysis with usage as dependent variable

Model		Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.
1	(Constant)	6.852	1.233		5.559	.000
	perceptions	.468	.068	.341	6.904	.000

a. Dependent Variable: usage

6.16 Analysis of Outcome variables

An analysis was conducted to establish the impact of adopting digital technologies on the expected benefits of working in SMEs. The results of the study are revealed that all six variables –performance, productivity, profitability, market share, customer satisfaction, sales improvement – are significant.

Analysis of Performance Scale (PE)

As shown in Table 6.103, the results revealed that for correlation coefficients between items for the performance. Scale 480- 1.000 which is generally greater that 0.3 (Tabachnick & Fidell, 2001). This indicates their suitability for factor analysis (FA) (Coakes, 2005).

Table 6.103 Correlations Matrix for Profitability

		PE 1	PE 1	PE 1	PE 1		PE 1
Correlations	**PE1**	1.000	.634	.593	.445		.480
	PE2	.634	1.000	.690	.560		.555
	PE3	.593	.690	1.000	.578		.594
	PE4	.445	.560	.578	1.000		.672
	PE5	.480	.555	.594	.672		1.000

KMO and Bartlett's Test for Performance Scale

As shown in Table 6.104, the results revealed that for KMO correlation items for the performance is 0.844. KMO correlation of 0.60 to 0.70 or higher is deemed sufficient for assessing the output of an EFA (Netemeyer, Bearden & Sharma, 2003). The result above the minimum acceptable level of 0.60., thus inducting sampling adequacy. Test of Bartlett's test of sphericity (chi-square = 894.466) was highly significant at $p< 0.000$. indicating adequate nature of relations between the variables. The data therefore appropriate.

Table 6:104 KMO and Bartlett's Test for Performance

KMO and Bartlett's Test		
Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.844
Bartlett's Test of Sphericity	Approx. Chi-Square	894.466
	df	10
	Sig.	.000

Factor Loading for Performance Scale

Factor Loading of scale items for Perception was examined. Factor loading below 0.4 are considered low and low- items should be suppressed (Field, 2005). In this study, the recommended cut oof factor loading of 0.5 ensured that all variables had practical significant (Hair et al., 2006). As shown in Table 6.105 the loading values of all five items exceed the cut-off level of 0.50.

Table 6.105 Factor Loading for Performance Scale

Component Matrix

Items	Component 1
PE1	.768
PE2	.848
PE3	.852
PE4	.797
PE5	.809

Extraction Method: Principal Component Analysis (PCA)

a. 1 component extracted.

Analysis of Productivity Scale (PRO)

As shown in Table 6.106, the results revealed that for correlation coefficients between items for the performance. Scale 0.494- 1.000. Whis is generally greater than 0.3. This indicates their suitability for factor analysis (FA) (Coakes, 2005).

Table 6.106 correlations Matrix for Productivity

		Prod1	Prod2	Prod3	Prod4	Prod5
Correlations	**Prod1**	1.000	.591	.488	.540	.515
	Prod 2	.591	1.000	.546	.521	.522
	Prod3	.488	.546	1.000	.547	.494
	Prod4	.540	.521	.547	1.000	.614
	Prod5	.515	.522	.494	.614	1.000

KMO and Bartlett's Test for Productivity

The results revealed that for KMO correlation items for the performance shown in Table 6.107, is 0 .853 and it clear that KMO correlation of 0.60 to 0.70 or higher is deemed sufficient for assessing the output of an EFA The result above the minimum acceptable level of 0.60., thus inducting sampling adequacy. Test of Bartlett's test of sphericity (chi-square = 720.181) was highly significant at p< 0.000. indicating adequate nature of relations between the variables. The data therefore appropriate.

Table 6:107 KMO and Bartlett's Test for Productivity

KMO and Bartlett's Test		
Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.853
Bartlett's Test of Sphericity	Approx. Chi-Square	720.181
	df	10
	Sig.	.000

Factor Loading for Productivity Scale

Factor Loading of scale items for Productivity was examined. Factor loading below 0.4 are considered low and low- items should be suppressed (Field, 2005). In this study, the recommended cut oof factor loading of 0.5 ensured that all variables had practical significant (Hair et al., 2006). As shown in Table 6.108 the loading values of all five items exceed the cut-off level of 0.50.

Table 6.108 Factor Loading for Scale

Component Matrix

Items	**Component 1**
Prod1	.789
Prod 2	.802
Prod3	.771
Prod4	.814
Prod5	.793

Extraction Method: Principal Component Analysis (PCA)

a. 1 component extracted.

Analysis of Profitability Scale (PROF)

As shown in Table 6.109, the results revealed that for correlation coefficients between items for the performance. Scale 0.476 - 1.000. Which is generally greater than 0.3? This indicates their suitability for factor analysis (FA) (Coakes, 2005).

Table 6.109 Correlations Matrix for Profitability

		Prof 1	Prof 2	Prof3	Prof4	Prof5
Correlations	**Prof 1**	1.000	.565	.474	.487	.476
	Prof 2	.565	1.000	.543	.510	.495
	Prof 3	.474	.543	1.000	.570	.503
	Prof 4	.487	.510	.570	1.000	.549
	Prof 5	.476	.495	.503	.549	1.000

KMO and Bartlett's Test for Profitability

As shown in Table 6.110, the results revealed that for KMO correlation items for the performance is .853. KMO correlation of 0.60 to 0.70 or higher is deemed sufficient for assessing the output of an EFA (Netemeyer, Bearden & Sharma, 2003). The result above the minimum acceptable level of 0.60., thus inducting sampling adequacy. Test of Bartlett's test of sphericity (chi-square = 661.332) was highly significant at p< 0.000. indicating adequate nature of relations between the variables. The data therefore appropriate.

Table 6:110 KMO and Bartlett's Test for Profitability

KMO and Bartlett's Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.853
Bartlett's Test of Sphericity	Approx. Chi-Square	661.332
	df	10
	Sig.	.000

Factor Loading for Profitability Scale

Factor Loading of scale items for Profitability was examined. Factor loading below 0.4 are considered low and low- items should be suppressed (Field, 2005). In this study, the recommended cut oof factor loading of 0.5 ensured that all variables had practical significant

(Hair et al., 2006). As shown in Table 6.111 the loading values of all five items exceed the cut-off level of 0.50.

Table 6.111 Factor Loading for Profitability Scale

Component Matrix

Items	**Component 1**
Prof 1	.763
Prof 2	.796
Prof 3	.791
Prof 4	.798
Prof 5	.770

Extraction Method: Principal Component Analysis (PCA)

a. 1 component extracted.

Analysis of Customers Satisfaction Scale (CS)

0As shown in Table 6.112, the results revealed that for correlation coefficients between items for the performance. Scale 0.392- 1.000. Which is generally greater than 0.3? This indicates their suitability for factor analysis (FA) (Coakes, 2005).

Table 6.112 Correlations Matrix for Customers Satisfaction

		CS 1	**CS 2**	**CS 3**	**CS 4**	**CS 5**
Correlations	**CS1**	1.000	.551	.500	.420	.392
	CS2	.551	1.000	.580	.530	.447
	CS3	.500	.580	1.000	.582	.471
	CS4	.420	.530	.582	1.000	.603
	CS5	.392	.447	.471	.603	1.000

KMO and Bartlett's Test for Customers Satisfaction

As shown in Table 6.113, the results revealed that for KMO correlation items for the performance is 0.828. KMO correlation of 0.60 to 0.70 or higher is deemed sufficient for assessing the output of an EFA (Netemeyer, Bearden & Sharma, 2003). The result above the minimum acceptable level of 0.60, thus inducting sampling adequacy. Test of Bartlett's test of sphericity (chi-square

= 673.324) was highly significant at p< 0.000. indicating adequate nature of relations between the variables. The data therefore appropriate.

Table 6:113 KMO and Bartlett's Test for Customers Satisfaction

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.828
Bartlett's Test of Sphericity	Approx. Chi-Square	673.324
	df	10
	Sig.	.000

Factor Loading for Customers Satisfaction Scale

Factor Loading of scale items for Customers Satisfaction was examined. Factor loading below 0.4 are considered low and low- items should be suppressed (Field, 2005). In this study, the recommended cut oof factor loading of 0.5 ensured that all variables had practical significant (Hair et al., 2006). As shown in Table 6.114 the loading values of all five items exceed the cut-off level of 0.50.

Table 6.114 Factor Loading for Customers Satisfaction Scale

Component Matrix

Items	**Component 1**
CS1	.726
CS2	.801
CS3	.810
CS4	.810
CS5	.744

Extraction Method: Principal Component Analysis (PCA)

a. 1 component extracted.

Analysis of Market Share Scale (MSH)

As shown in Table 6.115, the results revealed that for correlation coefficients between items for the performance. Scale 0.494- 1.000. Which is generally greater than 0.3? This indicates their suitability for factor analysis (FA) (Coakes, 2005).

Table 6.115 Correlations Matrix for Market Share

		MSH 1	MSH 2	MSH 3	MSH 4	MSH 5
Correlations	**MSH 1**	1.000	.606	.547	.536	.517
	MSH 2	.606	1.000	.579	.555	.530
	MSH 3	.547	.579	1.000	.567	.494
	MSH 4	.536	.555	.567	1.000	.697
	MSH 5	.517	.530	.494	.697	1.000

KMO and Bartlett's Test for Market Share

As shown in Table 6.116, the results revealed that for KMO correlation items for the performance is 0. 843. KMO correlation of 0.60 to 0.70 or higher is deemed sufficient for assessing the output of an EFA (Netemeyer, Bearden & Sharma, 2003). The result above the minimum acceptable level of 0.60, thus inducting sampling adequacy. Test of Bartlett's test of sphericity (chi-square = 818.143) was highly significant at p< 0.000. indicating adequate nature of relations between the variables. The data therefore appropriate.

Table 6:116 KMO and Bartlett's Test for Market Share

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.843
Bartlett's Test of Sphericity	Approx. Chi-Square	818.143
	df	10
	Sig.	.000

Factor Loading for Market Share Scale

Factor Loading of scale items for Market Share was examined. Factor loading below 0.4 are considered low and low- items should be suppressed (Field, 2005). In this study, the recommended cut oof factor loading of 0.5 ensured that all variables had practical significant (Hair et al., 2006). As shown in Table 6.117 the loading values of all five items exceed the cut-off level of 0.50.

Table 6.117 Factor Loading for Market Share Scale

Component Matrix

Items	Component 1
MSH 1	.793
MSH 2	.811
MSH 3	.788
MSH 4	.836
MSH 5	.804

Extraction Method: Principal Component Analysis (PCA)
a. 1 components extracted

Analysis of Sales Improvement Scale (SI)

As shown in Table 6.118, the results revealed that for correlation coefficients between items for the performance. Scale 0.494- 1.000. Which is generally greater than 0.3? This indicates their suitability for factor analysis (FA) (Coakes, 2005).

Table 6.118 Correlations Matrix for Sales Improvement

		SI 1	SI 2	SI 3	SI 4	SI 5
Correlations	**SI 1**	1.000	.534	.491	.427	.460
	SI 2	.534	1.000	.565	.418	.439
	SI 3	.491	.565	1.000	.551	.452
	SI 4	.427	.418	.551	1.000	.635
	SI 5	.460	.439	.452	.635	1.000

KMO and Bartlett's Test for Sales Improvement

As shown in Table 6.119, the results revealed that for KMO correlation items for the performance is 0.801. KMO correlation of 0.60 to 0.70 or higher is deemed sufficient for assessing the output of an EFA (Netemeyer, Bearden & Sharma, 2003). The result above the minimum acceptable level of 0.60, thus inducting sampling adequacy. Test of Bartlett's test of sphericity (chi-square = 659.169) was highly significant at p< 0.000. indicating adequate nature of relations between the variables. The data therefore appropriate.

Table 6:119 KMO and Bartlett's Test for Sales Improvement

KMO and Bartlett's Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.801
Bartlett's Test of Sphericity	Approx. Chi-Square	659.169
	df	10
	Sig.	.000

Factor Loading for Sales Improvement Scale

Factor Loading of scale items for Sales Improvement was examined. Factor loading below 0.4 are considered low and low- items should be suppressed (Field, 2005). In this study, the recommended cut oof factor loading of 0.5 ensured that all variables had practical significant (Hair et al., 2006). As shown in Table 6.120 the loading values of all five items exceed the cut-off level of 0.50.

Table 6.120 Factor Loading for Sales Improvement Scale

Component Matrix

Items	Component 1
SI 1	.748
SI 2	.762
SI 3	.795
SI 4	.787
SI 5	.773

Extraction Method: Principal Component Analysis (PCA)
a. 1 components extracted.

Analysis of Usage Effect on performance

The outcomes of the study are shown in Table 6.121. The results display that r-square (R^2) is the correlation coefficient squared (R^2=.120), which is also known as the coefficient of determination. The R^2 value indicates the percentage of total variation of Y (dependent variables) that is explained by the independent variables. In this analysis, 12% of the variability. In social science low R-Square values are often expected (Hossny, 2018) and does negate a significant predictor or change the meaning of its coefficient. Durbin-Watson statistics results inform us there is no problem concerning autocorrelation. For this study's data, the value is 1.534, so assumption has been met.

Table 6.121 Regression Model Summary for effect of usage on Performance

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
1	.347[a]	.120	.118	3.83585	1.534

a. Predictors: (Constant), usage
b. Dependent Variable: performance

In Table 6.122 below the results of correlation coefficients indicates a highly significant relationship between the dependent variable (Performance) and independent variable (USAGE). The significant level is 0.000.

Table 6.122 Coefficients for effect of usage on Performance

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	14.897	.722		20.631	.000
	usage	.320	.046	.347	7.037	.000

a. Dependent Variable: performance

Analysis of Usage Effect on Productivity

The outcomes of the study are shown in Table 6.123. The results display that r-square (R^2) is the correlation coefficient squared (R^2= 0.107), which is also known as the coefficient of determination. The R^2 value indicates the percentage of total variation of Y (dependent variables) that is explained by the independent variables. In this analysis, 11% of the variability. In social science low R-Square values are often expected (Hossny, 2018) and does negate a significant predictor or change the meaning of its coefficient. Durbin-Watson statistics results inform us there is no problem concerning autocorrelation. For this study's data, the value is 1.346, so assumption has been met.

Table 6.123 Regression Model Summary for effect of usage on Productivity

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
1	.327a	.107	.104	3.58793	1.346

a. Predictors: (Constant), usage
b. Dependent Variable: productivity

In Table 6.124 below the results of correlation coefficients indicates a highly significant relationship between the dependent variable productivity and independent variable (USAGE). The significant level is 0.000.

Table 6.124 Coefficients for effect of usage on productivity

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	16.025	.675		23.727	.000
	usage	.280	.043	.327	6.580	.000

a. Dependent Variable: productivity

Analysis of Usage Effect on Profitability

The outcomes of the study are shown in Table 6.125. The results display that r-square (R^2) is the correlation coefficient squared (R^2= 0.072), which is also known as the coefficient of determination. The R² value indicates the percentage of total variation of Y (dependent variables) that is explained by the independent variables. In this analysis, 0.72% of the variability. In social science low R-Square values are often expected (Hossny, 2018) and does negate a significant predictor or change the meaning of its coefficient. Durbin-Watson statistics results inform us there is no problem concerning autocorrelation. For this study's data, the value is 1.856, so assumption has been met.

Table 6.125 Regression Model Summary for usage effect on profitability

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
1	.268a	.072	.069	3.30376	1.856

a. Predictors: (Constant), usage

b. Dependent Variable: profitability

In Table 6.126 below the results of correlation coefficients indicates a highly significant relationship between the dependent variable profitability and independent variable USAGE. The significant level is 0.000.

Table 6.126 Coefficients for effect of usage on profitability

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	17.458	.622		28.071	.000
	usage	.207	.039	.268	5.286	.000

a. Dependent Variable: profitability

Analysis of Usage Effect on Customers Satisfaction

The outcomes of the study are shown in Table 6.127. The results display that r-square (R^2) is the correlation coefficient squared (R^2= 0.123), which is also known as the coefficient of determination. The R^2 value indicates the percentage of total variation of Y (dependent variables) that is explained by the independent variables. In this analysis, 12% of the variability. In social science low R-Square values are often expected (Hossny, 2018) and does negate a significant predictor or change the meaning of its coefficient. Durbin-Watson statistics results inform us there is no problem concerning autocorrelation. For this study's data, the value is 1.414, so assumption has been met.

Table 6.127 Regression Model for usage effect on Customers Satisfaction Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
1	.350a	.123	.120	3.55496	1.414

a. Predictors: (Constant), usage

b. Dependent Variable: Customers Satisfaction

In Table 6.128 below the results of correlation coefficients indicates a highly significant relationship between the dependent variable Customers Satisfaction and independent variable USAGE. The significant level is 0.000.

Table 6.128 Coefficients for effect of usage on Customers Satisfaction

Model		Unstandardized Coefficients		Standardized Coefficients		
		B	Std. Error	Beta	t	Sig.
1	(Constant)	15.630	.669		23.356	.000
	usage	.301	.042	.350	7.120	.000

a. Dependent Variable: Customers Satisfaction

Analysis of usage effect on Market Share

The outcomes of the study are shown in Table 6.129. The results display that r-square (R^2) is the correlation coefficient squared (R^2= 0.072), which is also known as the coefficient of determination. The R^2 value indicates the percentage of total variation of Y (dependent variables) that is explained by the independent variables. In this analysis, 12% of the variability. In social science low R-Square values are often expected (Hossny, 2018) and does negate a significant predictor or change the meaning of its coefficient. Durbin-Watson statistics results inform us there is no problem concerning autocorrelation. For this study's data, the value is 1.675, so assumption has been met.

Table 6.129 Regression Model for usage effect on Market Share Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
1	.269a	.072	.070	3.64296	1.675

a. Predictors: (Constant), usage

b. Dependent Variable: Market Share

Analysis of usage effect on Sales Improvement

The outcomes of the study are shown in Table 6.130. The results display that r-square (R^2) is the correlation coefficient squared (R^2= 0.064), which is also known as the coefficient of determination. The R^2 value indicates the percentage of total variation of Y (dependent variables) that is explained by the independent variables. In this analysis, 0. 64% of the variability. In social science low R-Square values are often expected (Hossny, 2018) and does negate a significant predictor or change the meaning of its coefficient. Durbin-Watson statistics results inform us there is no problem concerning autocorrelation. For this study's data, the value is 1.662, so assumption has been met.

Table 6.130 Regression for usage effect on Sales Improvement Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson

1	.254a	.064	.062	3.82740	1.662

a. Predictors: (Constant), usage

b. Dependent Variable: Sales Improvement

In Table 6.131 below the results of correlation coefficients indicates a highly significant relationship between the dependent variable Sales Improvement and independent variable USAGE. The significant level is 0.000.

Table 6.131 Coefficients for effect of usage on Sales Improvement

Model		Unstandardized Coefficients		Standardized Coefficients		
		B	Std. Error	Beta	t	Sig.
1	(Constant)	16.665	.720		23.130	.000
	usage	.227	.045	.254	4.986	.000

a. Dependent Variable: Sales Improvement

In Table 6.132 below the results of correlation coefficients of six outcomes (Performance, Productivity, Profitability, Customers satisfaction, Market share and Sales improvement). Indicates significant three variable has relationship with usage of AI including performance productivity and customers satisfaction. While the other three variable has no significant relationship.

Table 6.132 Coefficients for effect of usage on five Outcomes Coefficients

Model		Unstandardized Coefficients		Standardized Coefficients		
		B	Std. Error	Beta	t	Sig.
	(Constant)	-.155	1.633		-.095	.925
	Performance	.233	.056	.215	4.176	.000

Productivity	.185	.069	.159	2.686	.008
Profitability	.068	.074	.053	.917	.360
Customers satisfaction	.253	.070	.217	3.627	.000
Market share	.093	.077	.079	1.205	.229
Sales improvement	-.070	.074	-.062	-.940	.348

a. Predictors: (Constant), usage

6.17 Discussion the results of the hypothesis in this study

This thesis aimed to test the impact of several contexts on the adoption of digital technologies in Jordanian SMEs. The specific objective is to examine the effects of technological context, organizational context, political-environmental context, socio-cultural context, and demographic characteristics on the perception of owners/managers in SMEs in Amman, the capital of Jordan, to adopt and use digital technologies and effect this perception on outcome benefits. This thesis proposed a new conceptual model to examine four categories of determinants: technological, organizational, political-environmental, socio-cultural, and demographic. The primary strategy for testing hypotheses is based on the presumption that the result is invalid. Then, using concepts from statistics, the hypothesis testing technique analyses if the sample evidence supports the hypothesis (Schroeder, Sjoquist & Stephan, 2016). The hypothesis-testing process enables us to draw conclusions about the whole sample represented by our sample rather than simply the specific sample we choose. We must build some statistical theory to make inferential claims—that is, to conclude the population from a random sample. We thus explore a slightly less complicated example before moving on to evaluating hypotheses about population regression coefficients. As mentioned previously, a regression analysis was conducted to examine 26 hypotheses. The details of the hypothesis testing are discussed in more detail below.

Discussion of technological determinants hypotheses (H1to H3)

Technology's involvement in SMEs is a key factor influencing innovation and supporting how decisions are made to adopt new technologies (Alrawadieh, Alrawadieh, & Cetin, 2021). Three hypotheses were proposed to assess the impact of technological drivers on the perception and adoption of digital technologies by owners/managers in SMEs in Amman the capital of Jordan, as follows:

H1: Technology strategy has an impact on the perception towards digital technologies usage in the SMEs in Jordan.
H2: Employees IT knowledge has an impact on the perception towards digital technologies usage in the SMEs in Jordan.
H3: Technology infrastructure has an impact on the perception towards digital technologies usage in the SMEs in Jordan.

Results show that employees' IT knowledge (significant level of 0.031) and technology infrastructure (significant level of 0.012) significantly affect perception regarding digital technologies' usage. The other factor – technology strategy (significant level 0. 190), does not significantly affect perception concerning digital technology usage. The firm now places a high value on personnel's ability to employ innovative technologies and various applications (Verhoef, Broekhuizen, Bart, Bhattacharya, Qi Dong, Fabian & Haenlein, 2019). According to extensive studies, workers' knowledge and skills, including strategic thinking, problem-solving, and network communication abilities, are crucial to digitalization (Sousa & Rocha, 2019; Kashada, Li & Koshadah, 2018). To gain a competitive edge, businesses may innovate and continually develop their products and services with a solid and scalable IT infrastructure. IT infrastructure creates value for the business (Fink & Neumann, 2009). Owners/managers in SMEs in Jordan might feel that employees' IT knowledge and technology infrastructure are essential and that it is enough to motivate SMEs to adopt an innovation. In developing any knowledge and IT infrastructure regarding digital technologies adoption. As long as there is ample financial, technological, and motivational support, SMEs in Jordan may be willing to adopt and use digital technologies without being required to do so.

Discussion of organizational determinants hypotheses (H4 to H6)

Organizational context relates to the attributes and resources for an organization's technology adoption (Chau & Deng, 2018). The following three hypotheses are concerned with the impact of organizational drivers on the perception and adoption of digital technologies by owners/managers in SMEs in Amman the capital of Jordan, as follows:

H4: Managerial support has an impact on the perception towards digital technologies usage in the SMEs in Jordan
H5: Training has an impact on the perception towards digital technologies usage in the SMEs in Jordan
H6: Reward system has an impact on the perception towards digital technologies usage in the SMEs in Jordan.

Results of the regression analysis presented in Table 6.98 indicate that the impacts of managerial support (significant level of 0.000), Training (significant level of 0.000) and reward system (significant level of 0.012) are statistically significant, so these hypotheses are supported in the model. Results show that three factors – managerial support, training and reward system are statistically significant. It is true in the work environment that, as reward system increase, individual adoption and usage levels also rise. reward system positively influences the adoption and usage of any new technology. Training assists individuals in how to use new technology. It is projected that managerial support will encourage digital technologies, including big data and other information systems (Park & Kim, 2021). According to Masudin, Aprilia, Nugraha, and Restuputri (2021), managers should encourage technological innovation by using original methods to oversee organizational activities. Selvarajah, Le, and Sukunesan (2019) noted the value of training in developing SMEs' capacity to perform better. The chosen training factor's primary goal is to help SMEs improve their human resource capabilities and understand how training affects how they see digital technology. For employees who adopt and use digital technologies, a firm may offer rewards in the form of goods or other benefits (Talukder, 2014). Employees are more likely to be inspired to complete tasks not because they enjoy doing so but because of the incentive attached (Adler, 2013; Roland & Jean, 2003; Seun, Kalsom, Bilkis & Raheem, 2017).

Discussion of political – environmental determinants hypotheses (H7 to H 9)

Environmental contexts are external factors that impact technology adoption, such as pressures from suppliers, and external supports (Chau & Deng, 2018). Government policy, regulations, and competitive pressure affect how quickly IT is adopted (Park & Kim (2021). The following three hypotheses are concerned with the impact of political – environmental drivers on the perception and adoption of digital technologies by owners/managers in SMEs in Amman the capital of Jordan, as follows:

H7: Government support has an impact on the perception towards digital technologies usage in the SMEs in Jordan
H8: Government regulations has an impact on the perception towards digital technologies usage in the SMEs in Jordan
H9: Competitive pressure has an impact on the perception towards digital technologies usage in the SMEs in Jordan.

Results of the regression analysis presented in Table 6.79 indicate that the impacts of government support (significant level of 0.008) are statistically significant, government regulations (significant level of 0.469) are statistically not significant, competitive pressure (significant level of 0.162) is statistically not significant. Results show that only government support significantly affects perception regarding the adoption of digital technologies. The other two factors – government regulations and competitive pressure – do not significantly affect perception concerning adoption of digital technologies. Owners/managers in SMEs might feel that government support is crucial, and that it is enough to motivate SMEs to adopt an innovation. In the development of any sort of regulations and policies regarding digital technologies adoption, it might not be necessary to require employees to adopt a new system; as long as there is ample support that is financial, technological and motivational in nature, employees may be willing to adopt the digital technologies without being required to do so. SMEs are not exempt from the government's crucial role in promoting innovation uptake (Ediriweera & Wiewiora, 2021). Governments have seen SMEs as critical to economic growth and sustainability because of their contribution to job creation, social cohesion, poverty alleviation, economic development, and innovation (Qalati, Li, Ahmed, Mirani & Khan, 2021). Government-funded training programmes can assist SME managers, owners, and staff in embracing technology (Shaikh, Kumar, Syed, Ali & Shaikh, 2021). May the owners/managers in SMEs in Jordan have concerned about the government regulations because the difficulty of secure distributed data management and sharing, mainly what might contain personally identifiable information, is the focus of the theme of data privacy and protection (Dorr, Greenberg, Fontana, Przybocki, Le Bras, Ploehn, & Chang, 2015). Digital technology can enable SMEs to transform the structure of their industry or business and utilize new techniques to outperform their competitors (Müller, Buliga & Voigt, 2018).

Discussion of socio-cultural determinants hypotheses (H10 to H12)

Diverse factors influence the spread of renewable digital technologies but incorporating the social and cultural components would enrich our understanding of how digital technologies are adopted in SMEs (Clohessy, Acton & Rogers, 2018). The following three hypotheses are concerned with the impact of socio-cultural determinants on the perception and adoption of digital technologies by owners/managers in SMEs in Amman the capital of Jordan, as follows:

H10: Peer support has an impact on the perception towards digital technologies usage in the SMEs in Jordan
H11: Social network has an impact on the perception towards digital technologies usage in the SMEs in Jordan
H12: Religious beliefs has an impact on the perception towards digital technologies usage in the SMEs in Jordan.

Results of the regression analysis presented in Table 6.79 indicate that the impacts of peer support (significant level of 0.128) are statistically not significant on perception, social network (significant level of 0.017) are statistically significant on perception, religious beliefs (significant level of 0.003) are statistically significant on perception. Social network refers to how members of other firms or those of social networks are impacted by workers (Gupta, 2021). A member is more likely to be exposed to novel concepts and artefacts the more informal information is exchanged among participants (Talukder, Alyammahi, Quazi, Abdullah & Johns, 2019). An information technology application that best meets the interests of market participants is the social networking platform (Turaev & Ganiev, 2021). Assessment of employees' religious beliefs as a vital component of workplace practices has been initiated by management researchers (Alsheddi, Sharma & Talukder, 2020). Many people have viewed religion as a complex idea that affects people's beliefs, way of life, and sense of self and discovered that Muslim consumers were more innovative and practical than non-Muslim consumers (Sun, Goh, Fam & Xue, 2012).

Discussion of demographics characteristics hypotheses (H13 to H19)

Prior studies on the significance of demographics reveal that gender, age, level of education and other factors are critical determinants in predicting user attitude towards adopting digital products or services (Chawla & Joshi, 2021). The following seven hypotheses are concerned with the impact of demographics drivers on the perception and adoption of digital technologies by owners/managers in SMEs in Amman the capital of Jordan, as follows:

H13: Gender difference has an impact on the perception towards digital technologies usage in the SMEs in Jordan
H14: Age difference has an impact on the perception towards digital technologies usage in the SMEs in Jordan
H15: Qualifications have an impact on the perception towards digital technologies usage in the SMEs in Jordan.
H16: Employment experience has an impact on the perception towards digital technologies usage in the SMEs in Jordan.
H17: Type of industry has an impact on the perception towards digital technologies usage in the SMEs in Jordan.
H18: Number of employees has an impact on the perception towards digital technologies usage in the SMEs in Jordan
H19: Role in the business has an impact on the perception towards digital technologies usage in the SMEs in Jordan.

The results the demographics determents analysis show that five factors H14, H15, H16, H18 and H19 significantly affect perception to usage of digital technologies applications: Age (significant level 0.000), qualifications (significant level 0.009), experience (significant level 0.000), employees (significant level 0.000), Role (significant level 0.000). The analysis shows that two factors H 13 and H17 not significant affect perception to usage of digital technologies applications. Gender (not significant level 0.480), Industry (Not significant level 0.381), It appears that two factors (gender and type of industry) are not supported in the model; the results of these factors are shown in Table 6.79. Several empirical studies have failed to investigate the effects of gender as a moderator (Kapser, Abdelrahman & Bernecker, 2021). The Gender factor contradicts (Chawla & Joshi, 2021) who explored that gender differences have an impact towards adopting digital products or services. Reasons that might inhibit the adoption of technologies include lack of knowledge, standardization, and insufficient cooperation in many firm segments (Ko, Kincade & Brown, 2000). The type of industry factor contradicts (Oliveira, Thomas & Espadanal, 2014), who discovered that addresses performance variance that may arise due to industry-specific climate and market rivalry conditions. Conversely, top management executives' ignorance of IT capabilities discourages adoption (Huang & Rust, 2018). Top management's knowledge, aptitude, and use of mobile devices thus positively affect adoption determinants (Ho & Lim, 2018; Kübler, Pauwels, Yildirim, Fandrich, 2018). Hashim (2007) examined the relationship between top management executive experience and SMEs' technology adoption. He noticed that as SMEs have more IT experience, they grow and fully grasp how IT may progress in commercial activities.

Discussion of Perception hypotheses (H20)

The acceptance of digital technologies is impacted by users' perception to them (Chawla & Joshi, 2021). The below hypothesis was designed to examine if an employee’s perception impacts on the adoption of digital technologies and their usage.

H 20: Perception has an impact on the perception towards digital technologies usage in the SMEs in Jordan.

The findings show that there is a strong relationship between perception and usage behavior, consistent with previous research findings (Talukder, 2011; Davis, 1989; Taylor & Todd, 1995; Lam et al., 2007; Al-Gahtani & King, 1999). H20 significantly affect perception to usage of digital technologies applications are high significant level (0.000) and this means H20 is supported the model. The result does agree with that Koontz and Weihrich (2005) who pointed out that the attitude towards technology is a pre-condition for accepting the technology. A positive perception of digital technologies and a acknowledgement of the strategic role of them from perceived usefulness, perceived ease of use is an important symptom of readiness and a particular indicator of willingness to adopt digital entrepreneurship in SMEs (Chatterjee, Chaudhuri, Vrontis & Basile, 2021).

Discussion of outcomes hypotheses (H21 to H26)

For SMEs, digital technology has advantages in terms of improved performance, productivity, and profitability. More jobs are created, and better goods and services are sold as a result (Atkinson & McKay, 2007). Due to the need for more clients, digital technology has been more prevalent in SMEs recently. Six hypotheses were developed to test the impact of the adoption and usage of digital technologies on benefits for Jordanian SMEs. They are performance, productivity, profitability, market share, customer satisfaction and sales improvement.

H21: Usage of digital technologies has an impact on performance in Jordan SMEs.
H22: Usage of digital technologies has an impact on productivity in Jordan SMEs.
H23: Usage of digital technologies has an impact on profitability in Jordan SMEs.
H24 Usage of digital technologies has an impact on market share in Jordan SMEs.
H25: Usage of digital technologies has an impact on customer satisfaction in Jordan SMEs.
H26 Usage of digital technologies has an impact on sales improvement in Jordan SMEs. organizations.

The results show that adopting digital technologies significantly affects all the outcome variables (significant level 0.000) in Jordanian SMEs in Amman. The results are supported by many studies. It appears that the positive effects of digital technologies on the performance of SMEs consolidating and aligning information technology will strengthen their core capabilities and improve business performance (Trinugroho, Pamungkas, Wiwoho, Damayanti & Pramono, 2021; Kumar & Ayedee, 2021). Increasing productivity, which is defined as the ratio of inputs (i.e., resources needed to produce outputs) to outputs (i.e., goods or services), is a strategic objective for every organization (Lacka, Wong & Haddoud, 2021). Since productivity is a key factor in economic effectiveness and growth, it is crucial statistical data for many international comparisons and country assessments (OCDE, 2011). Digital technologies boost output and open new possibilities for producing superior items (Kumar & Ayedee, 2021). Profitability is a ratio that assesses firms' ability to create profits and income (Som & Goel, 2021). Competition for market share brought about by technological progress has fueled smaller innovative entrepreneurial enterprises and the sustainability and profitability of larger businesses (Das, Kundu & Bhattacharya, 2020). People's lifestyles and consumption behaviors are shifting due to newly created and deployed technology, which substantially impacts business-customer relationships (Zouari & Abdelhedi, 2021). Ghobakhloo and Ching (2019) stated that digital technologies boost performance by contributing to sales improvement, improving customer satisfaction and supplier connections, and promoting the business's capabilities (Çallı & Çallı, 2021).

6.18 Summary of the hypothesis testing

The following summary of the hypothesis testing is in below Table 6.133. The finding of this research shows that seventeen of twenty-six hypotheses met the significance level.

Table 6.133 Summary of the Hypothesis Testing

Hypothesis	*Significance Level*	*Decision*
Technological Hypothesis		
(1) Technology strategy	0.190	REJECT
(2) Employees IT knowledge	0.012	DON'T REJECT
(3) Technology infrastructure	0.031	DON'T REJECT
Organizational Hypothesis		
(4) Managerial support	0.000	DON'T REJECT
(5) Training	0.000	DON'T REJECT
(6) Reward system	0.012	DON'T REJECT
Political-Environmental Hypothesis		
(7) Government support	0.008	DON'T REJECT
(8) Government regulations	0.469	REJECT
(9) Competitive pressure	0.162	REJECT
Socio-Cultural Hypothesis		
(10) Peer support	0.128	REJECT
(11) Social network	0.017	DON'T REJECT
(12) Religious beliefs	0.003	DON'T REJECT
Demographics Hypothesis		
(13) Gender	0.480	REJECT
(14) Age	0.000	DON'T REJECT

(15) Qualification	0.009	DON'T REJECT
(16) Employment Experience	0.000	DON'T REJECT
(17) Type of Industry	0.381	REJECT
(18) Number of Employees	0.000	DON'T REJECT
(19) Role	0.002	DON'T REJECT
Perception Hypothesis		
(20) Perception	0.000	DON'T REJECT
Expected outcomes Hypothesis		
(21) Performance	0.000	DON'T REJECT
(22) Productivity	0.008	DON'T REJECT
(23) Profitability	0.360	REJECT
(24) Customers satisfaction	0.000	DON'T REJECT
(25) Market share	0.229	REJECT
(26) Sales improvement	0.348	REJECT

6.19 Conclusion

This chapter focused on the empirical testing of the proposed model chosen to explain digital technology adoption in the Jordanian SMEs in Amman. Statistical analysis shows that the proposed conceptual model contributes to a better understanding of the determinants driving SMEs' acceptance of technological innovation in the workplace. The empirical study showed the effects of technological, organizational, political-environmental, and socio-cultural contexts on SMEs' acceptance of digital technologies. Three technological context factors – namely, technology strategy, employees' IT knowledge, and technology infrastructure – were incorporated into the model. Both variables' employees' IT knowledge and technology infrastructure have been found to affect perceptions and acceptance of innovation. The technology strategy variable did not significantly affect owners' or managers' perception of digital technologies and usage. Three organizational context factors—namely, managerial support, training, and reward system—and empirical findings revealed that three variables significantly affected owners' or managers' perceptions of digital technologies and usage. Government support, regulations, and competitive pressure are three political-environmental context factors. Empirical findings revealed that only one variable—government support—

significantly affected owners' or managers' perceptions towards digital technology adoption and usage.

Empirical findings revealed that only social networks and religious beliefs significantly affected owners' or managers' perceptions of digital technologies' adoption and usage, while peer support did not. Finally, demographic variables were tested to establish whether they shape perceptions of digital technology adoption. Results indicate that five of seven factors, namely age, qualification, experience, experience at work and the number of employees, were significant. At the same time, gender and industry type did not greatly support the model. Also, the results show the effect of the perception of adopting and using digital technologies on the outcomes for SMEs. The results of the data findings were described in terms of correlations, regressions, and tabulations. Seventeen out of twenty-six study variables significantly impacted the use and adoption of digital technology and related applications. In contrast, nine were found to have no significant effect. The next chapter summarizes the research findings and the contributions, implications, and limitations of this thesis. Moreover, recommendations for future research will be suggested.

CHAPTER SEVEN: CONCLUSION, IMPLICATIONS AND RECOMMENDATIONS

7.1 Introduction

This thesis responds to the call for more in-depth and comprehensive research on SMEs' adoption of digital technologies and the determinants influencing this process. To increase the adoption rate of in the SMEs, owners/managers should recognize all the technological, organizational, political-environmental, socio-cultural, religious and demographic determinants or matters that influence how this occurs. Adopting digital technologies can create efficiencies in their processes, reduces costs, retain customers, maintain a competitive advantage over competitors (Zide & Jokonya, 2022) and generate opportunities (Gabrielsson, Fraccastoro, Ojala & Rollins, 2022). Hence, this thesis tested an enhanced conceptual model for owners/managers of SMEs to take up. This topic was explored and tested using a quantitative questionnaire survey completed by 364 owners/managers at particular SMEs in Amman, the capital of Jordan. This chapter summarizes how the study answered the research questions; it also presents conclusions, including the theoretical contribution and implications for policy and practice for the future. Lastly the research limitations of the study are explained and an overview of the opportunities for future directions for research on this topic is given.

7.2 Summary of the Research

Digital technology is now ubiquitous at the individual and business levels, as shown by the integration of computer-based work in the public and private sectors, and a whole range of services and industries (Lee & Trimi, 2021; Paiola, Schiavone, Grandinetti & Chen, 2021). The applications of digital technologies can enhance decision-making, effectiveness, and the quality of services that all help to improve revenues, reduce costs and save time (Zong, Yuan, Montenegro-Marin & Kadry, 2021). Staff members must appropriately use innovative technologies for themselves and their organizations to get the benefits (Grand View Research, 2022; Talukder, 2014). Rogers (2003) expresses adoption as the decision to employ innovation fully as the best course of action. However, limited research has been conducted on the determinants of innovative adoption, particularly in the Middle East. There is a gap in the current literature in that we need to learn more about how or why managers/owners embrace innovative technologies and what this means for the economies and societies in this part of the world. Hence the adoption of innovation in SMEs in Jordan is significant because its economy relies on SMEs, and they employ people, generate income and give communities a sense of purpose (Muriithi, 2017; Mashal, 2018; Chege & Wang, 2020; Alkhodary, 2021).

Advances in digital technologies are at the forefront of the innovation process and has produced economic growth, in the form of new opportunities, including reducing barriers to e-commerce entry and inclusion in global value chains, e.g., Skype, Dropbox, Google, PayPal, Linked In, and Amazon (OECD, 2017; Oliveira, Kakabadse & Khan, 2022). Research questions and hypotheses were proposed to explain the determinants that affect and determine the use and adoption of technological innovation by managers/owners in SMEs in Jordan. Four overarching questions were devised to examine these institutions' practices as follows:

1. What is the impact of technological, organizational, political-environmental and socio-cultural determinants on SMEs' perceptions of digital technologies?
2. What is the impact of demographic characteristics on SMEs' perceptions of digital technologies?
3. What is the impact of SMEs' perceptions of digital technologies on the usage level?
4. What are the expected benefits to Jordanian SMEs from using digital technologies?

The finalized conceptual model consists of five categories (technological, organizational, political-environmental, socio-cultural, and demographic characteristics) to measure their effect on the perceptions regarding digital technologies. In the second stage, the model tested the impact of perception on this digital technologies' usage, while the third stage investigated the effects of using digital technologies on the perceived benefits.

This research used an online quantitative method to investigate the effect of technological, organizational, political-environmental, socio-cultural, and demographic characteristics on the acceptance of technological innovations by owners/managers in SMEs in Amman. The questionnaire which sought numerical data was developed to suit this thesis's study objectives and aims. As well, the validity and reliability of the questionnaire items were first tested using a pilot study to identify and modify any things which respondents might misunderstand, skip over, or answer unsuitably. Data was collected from owners/managers of the Jordanian SMEs to test the proposed conceptual model and how it could or could not explain the determinants that affect the adoption of digital technologies. The study calculated frequency distribution and percentage, and descriptive statistics for several cross-tabulations were done. This study conducted correlation matrix and inter-correlation tests for reliability, validity and ANOVA-based outcomes. Multiple regression analyses were carried out to connect groups within the same category and the variances between them to test the proposed model. It appears that technology strategy determinant from the technological context, government regulations and competitive pressure determinants from the organizational context and peer support determinant from the socio-cultural context had no significant effect on the perceptions to adoption digital technologies in Amman's businesses.

The study employed the quantitative method which led to a better understanding of the determinants that affect embracing digital technologies and AI. Of the 26 hypotheses selected for this study, seventeen were supported but nine were not: two variables from the technological context category, three variables from the organizational context category, one variable from the political-environmental context category, two variables from the socio-cultural context category, five demographic variables, the perception variable and three from the expected benefits. The nine rejected hypotheses comprise one technological context category, two from the political-environmental context category, one from the socio-cultural context category, two from demographic variables and three from the expected benefits. This result is presented in Table 7.1 below.

Table 7.1 Summary of results for hypotheses

Hypothesis	**Path Direction**	**Significance Level**	**Decision**
Technological Hypothesis			
(1) Technology strategy	TS → PER	0.190	REJECT
(2) Employees IT knowledge	EK → PER	0.012	DON'T REJECT

(3) Technology infrastructure	TI → PER	0.031	DON'T REJECT
Organizational Hypothesis			
(4) Managerial support	MS → PER	0.000	DON'T REJECT
(5) Training	TR → PER	0.000	DON'T REJECT
(6) Reward system	RS → PER	0.012	DON'T REJECT
Political–Environmental Hypothesis			
(7) Government support	GS → PER	0.008	DON'T REJECT
(8) Government regulations	GR → PER	0.469	REJECT
(9) Competitive pressure	COP → PER	0.162	REJECT
Socio-Cultural Hypothesis			
(10) Peer support	PS → PER	0.128	REJECT
(11) Social network	SN → PER	0.017	DON'T REJECT
(12) Religious beliefs	RB → PER	0.003	DON'T REJECT
Demographics Hypothesis			
(13) Gender	GN → PER	0.480	REJECT
(14) Age	AG → PER	0.000	DON'T REJECT
(15) Qualification	QE → PER	0.009	DON'T REJECT
(16) Employment experience	EW → PER	0.000	DON'T REJECT
(17) Type of Industry	TI → PER	0.381	REJECT
(18) Number of Employees	NE → PER	0.000	DON'T REJECT
(19) Role	JP → PER	0.002	DON'T REJECT
Perception Hypothesis			
(20) Perception	RB → UDT	0.000	DON'T REJECT
Expected outcomes Hypothesis			
(21) Performance	UDT → PERF	0.000	DON'T REJECT
(22) Productivity	UDT → PROD	0.008	DON'T REJECT
(23) Profitability	UDT → PROF	0.360	REJECT
(24) Customers satisfaction	UDT → CS	0.000	DON'T REJECT
(25) Market share	UDT → MS	0.229	REJECT

(26) Sales improvement	UDT → SI	0.348	REJECT

Table 7.2 Summary of the research questions addressed

Research Questions	Summary of the results
1. What is the impact of technological, organizational, political-environmental, and socio-cultural determinants on SMEs' perceptions of digital technologies?	Two determinants as part of the technological context were found to significantly impact the perceptions of SMEs owners/managers regarding digital technologies, i.e., Employees' IT knowledge and Technology infrastructure. At the same time, the organizational context, including managerial support, Training and Reward system, has a significant impact on the perceptions of SMEs owners/managers. Government support as part of the political-environmental context is the only determinant with a significant effect on the perceptions of SMEs owners/managers. Social network and religious beliefs determinants under socio-cultural context significantly impact the perception of SMEs owners/managers. There were four determinants that did not significantly influence the perceptions of SMEs owners/managers towards digital technologies: one technological context category is technology strategy, two from the political-environmental context category are Government regulations and Competitive pressure, one from the socio-cultural context category is peer support. Eight of the twelve determinants did help shape SMEs' perceptions of digital technologies.
2. What is the impact of demographic characteristics on SMEs' perceptions of digital technologies?	Five demographic characteristics were found to have a significant impact on the perceptions of SMEs towards digital technologies, i.e.., age, qualification, experience, employment experience, number of employees and role in the business. Two from demographic variables -

	gender and type of industry - did not significantly impact the perceptions of SMEs owners/managers.
3. What is the impact of SMEs' perceptions of digital technologies on usage level?	As for the third question, perceptions have shown a strong influence on the level of digital technology-AI usage. Pearson's correlation confirmed there was a significant positive correlation between the independent variable (usage) and dependent variable (perception).
4. What are the expected benefits to Jordanian SMEs from usage and adopting digital technologies?	The results showed that SMEs' performance, productivity and customer satisfaction did have a strong relationship with the usage of digital technologies-AI. At the same time, the other expected outcomes, namely profitability, market share and sales improvement, are not significantly related to digital technologies-AI usage.

7.3 Study Contribution

This study makes significant theoretical and practical contributions to the topic. Firstly, it is one of the most up-to date analyses of the determinants that guide the adoption and use of digital technologies in Jordanian SMEs. Secondly, it broadens our understanding of the determinants affecting innovations technological adoptions. Thirdly, it develops a coherent model of technology adoption to examine what these determinants actually do. The study also makes a practical contribution by describing the implications for government, management and other key stakeholders.

Theoretical contribution

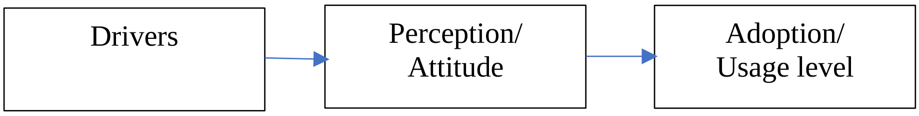
Many studies have been conducted on technological innovation adoption in developed countries, but the extent to which Industry 4.0 technologies may have diffused in developing economies remains unclear (Delera, Pietrobelli, Calza & Lavopa, 2022). Only a few studies have been done on digital technologies in developing countries, for instance in the Middle

Eastern region. These nations are still falling behind in the general implementation of technology (AlKhouri, 2012; Balta-Ozkan, Davidson, Bicket, & Whitmarsh, 2013a; Haque, Chin, & Debnath, 2013; Komninos, Pallot, & Schaffers, 2013; Talukder, Alsheddi, Sharma & Islam, 2020; Thabit, Aissa & Jasim, 2021). There is a gap in the literature indicating a lack of adequate knowledge of what drives the adoption of technological innovation in these countries (Balta-Ozkan, Davidson, Bicket, & Whitmarsh, 2013a).

This study integrates technological, organizational, political-environmental, and socio-cultural contexts into a coherent theoretical model. This combination of variables goes beyond previous research to bring together all the relevant determinants that may affect the perception and use of digital technologies in workplace settings. The study examines the relationship between digital technology adoption and the drivers that affect and determine the adoption and continued use of technologies by small and medium-sized enterprises. The study addresses several determinants and analyses them to identify the level of impact each one has and the differences; consequently, it contributes to knowledge and the broader theoretical understanding of the given phenomenon. Organizational context used in this study (managerial support, training, reward system) and socio-cultural determinants such as peer support, social network, and religious beliefs was very critical. The political-environmental determinants such as government support, government regulations and competitive pressure, in addition to demographic determinants, have not been explored in previous studies.

In Middle Eastern countries, socio-cultural and religious values significantly impact employees' daily activities and has ramifications for the SME context. The existing technology adoption-related theories and models lack analyses about the impact on organizational performance when they refer to adopting technology. For example, the theory of reasoned action (TRA), theory of planned behavior (TPB), the technology acceptance model (TAM), the unified theory of acceptance and use of technology (UTAUT), DeLone and McLean information systems success model (IS success model), diffusion of Innovations (DOI) theory and technology-organization-environment (TOE) frameworks did not have any outcome variables. Only a few studies have extended these models by adding one or two variables (Chang & Cheung, 2001). The proposed model for this thesis provides a framework for future research on innovation adoption to consider. Figure 7.1 below provides a new pathway in technology adoption-related research.

Most of the theories have three steps in their model structure:



In my research I have added one more step in the model to identify the perceived outcome.

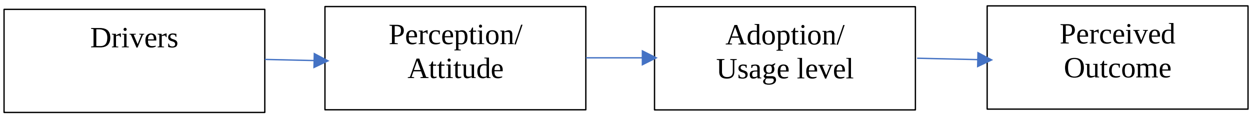


Figure 7.1: Steps to identify new pathway in technology adoption.

One of the significant contributions of this thesis lies in combining and applying different theories and models developed in Western and advanced nations to study technological innovation in a developing market economy. The novelty of this research lies in the specification and development of five categories as the predictive constructs impacting perceptions, usage, and benefits of the digital technologies used by SMEs in Amman, Jordan. The combination of political-environmental and socio-cultural contexts into a single study goes beyond what previous research has accomplished, generating a sophisticated statistical analysis to better understand each determinant's acceptance of digital technologies in a region that was rarely the focus of past research. The survey respondents were actual users of digital technologies, i.e., managers/owners of SMEs.

Contribution to Knowledge

This study has contributed to new knowledge by researching a range of technological, organizational, political-environmental, and socio-cultural contexts that shape SMEs' perceptions of adopting digital technologies in Jordan and what this may mean for other Middle East countries. This may be a future source of reference for studies to be done elsewhere in the Middle east and north Africa. The analysis helped to create an excellent understanding of the determinants that influence organizations' adoption and use of digital technologies.

The methodology employed in this research makes a significant contribution to knowledge. Primary data was collected using a survey questionnaire to test the proposed advanced enhanced model. Questionnaires were then discussed with expert analysts on technology adoption stated previously, and data were investigated using the SPSS 27 package. Several cross-tabulations were performed. Frequency distribution and percentages were calculated. Reliability and validity were tested. This research tested the proposed model by multiple regression analysis conducted on the collected data. The study tested the enhanced model, and the finding supported most of the hypotheses. The research is expected to understand better how technological, organizational, political-environmental, and socio-cultural determinants affect owners'/managers technological innovation adoption behaviors. Middle East nations are a perfect example of where technological, organizational, political-environmental, and socio-cultural prevail in all facets of an individual's life.

7.4 Implications of the study

This study provides useful insights for practitioners or business managers who are regularly involved in the implementation of new technologies. It highlights a few major aspects for managers and practitioners, or policymakers as follows.

Implications for the Jordanian government

The research has important implications for the Jordanian government and policymakers regarding implementing technological innovation. Jordan sees digital transformation as a basis for the country's economy. Given the relative importance of SMEs in many economies, the government has taken steps to guarantee this sector is not left behind as the digital era unfolds and spreads. According to Adaileh and Alshawawreh (2021), Jordan's government revealed the REACH 2025 Vision in 2016, and it has taken several significant steps to transition industries, businesses, and individuals to becoming virtually digital by 2025. REACH 2025 is essential for Jordan's future economy, enabling people, industries, and businesses to implement digital solutions and establish a solid foundation. Globalization and technological change have ushered in a shift in how companies and governments function in the Middle East and beyond in the last few decades. Hence, Jordan is moving away from perceiving ICTs as a separate industry and digitizing the whole economy while focusing on specific markets and global value chains (Adaileh & Alshawawreh, 2021).

According to Al-Okay, Alqudah, Al-Qudah, and Alkhwaldi (2022), the Jordanian public sector is divided into ministries, independent bodies, and public universities. Regarding the ministries, 25 ministries vary in their development and responsibility, deemed as the backbones of the public sector. In addition to these 25 ministries, there are 27 independent bodies, and the third entity type is public universities (ten universities); the Jordanian public sector includes 297 entities in the Kingdom of Jordan. This study will also assist these Jordanian government institutions in developing policies to implement digital technologies. The research helps the Jordanian government make investment decisions using digital technologies that enable businesses to take up new technologies, particularly when the SMEs do not have enough capital to do so. The most crucial problems are compounded by inadequate preparation, a lack of objectives, and changing objectives throughout project execution (Alkhlaifat, Abdullah & Al-Khamaiseh, 2021).

Government officials can utilize the results of this study to understand and implement technological innovation policies that improve cost-effectiveness, workplace efficiency and produce good service quality outcomes. The results of this thesis show that embracing digital technologies enhances productivity and performance in the government sector if interdicted in the right way and supports Jordan's government REACH 2025 strategy. This research produced a practical guideline and strategic document based on finding that could help the Jordanian government, specifically the Ministry of Digital Economy and Entrepreneurship (MODEE) as it is responsible for the country's digital economy, entrepreneurship, and getting staff and clients updated on new business practices. MODEE works in collaboration with other government agencies, such as digital infrastructure, digital leadership, digital platforms, digital skills, and digital financial services (MODEE, 2021). Despite the rapid growth in the world's use of ICTs, business activities in Jordan and most developing countries are still limited and slowly evolving.

Implications for Jordanian SMEs' Management Personnel

This research has significant implications for management personnel working for SMEs in Jordan. These managers no matter what their classification must consider more carefully the determinants impacting the practical usage of digital technologies in the workplace. The developed proposed, validated model can also assist SME owners/managers identify the determinants that will lead to meaningful digital technologies adoption so that it generates productivity, profitability, share market, customer satisfaction and sales improvement. Receiving feedback on the importance of enlightening the businesses' competitiveness and how digital technologies could improve work procedures will help managers introduce training courses to their employees about how digital technologies can be deployed effectively.

The inference drawn from the outcomes will encourage owners/managers in SMEs to make the right decision and advice more progressive policies concerning the efficient usage and implementation of digital technologies such as AI. This study highlights the potential influences of such adoption on Jordanian SMEs to assist in making decisions. It found that a high level of competitiveness can be maintained through digital technologies by SMEs and their rivals in Jordan. Socio-cultural context is essential to informing positive owners/managers' perceptions of digital technologies. Managers of SMEs may encourage 'getting the word out' through professional social events. That leads to exposure to word-of-mouth communication with their workers and external parties about digital technologies, to generate positive perceptions about innovations and lead to acceptance and effective use through workshops, seminars, etc.

Jordanian SMEs can benchmark practices for digital technologies, through effective information sharing and collaborative efforts, among departments and trading partners. This highlights the advantages and enhancements realized through digital technologies and the shift from the intention to adopt to actual successful digital technology deployment. This will require proper preparation of several initiatives concerning the value and importance of digital technologies to enterprises. SME owners/managers will be inclined to understand why their businesses lag behind larger firms in Jordan or elsewhere in the world through this study's findings. The SMEs manager's recognition of government support and reward systems plays a crucial role in meeting the enterprises' technological innovation needs. SMEs' managers require government regulatory support and a financial reward system. Owners/managers interested in testing, understanding, and implementing digital technology their businesses will be assisted by the findings documented here. It will also help them respond more quickly to changes in their external environment and reduce risk and uncertainty, or at least identify what they are and how to work around them. Owners/managers can plan and prepare for digital technologies and ensure that doing so enables a smooth and less costly transfer of processes.

Implications for SMEs as organizations

Firms worldwide have been continually trying to keep up with changing technological innovations and circumstances. The acceptance of digital technologies has resulted in significant changes in how business organizations and their staff operate, including improved operational efficiencies (Oliveira, Kakabadse & Khan, 2022). It is, therefore, essential to continuously monitor the operating forces influencing the innovation adoption procedure, especially in a country like Jordan. based on the findings, Jordanian SMEs should emphasize managers' cooperation to improve the rate of technology implementation. In the Middl East countries, these cultures put a high premium on the collective mindset and working together to get things done. Here there is an excellent emphasis on supporting each other. Managers in organizations will benefit from this tradition in developing new policies for accepting and using digital technologies in Jordanian SMEs.

7.5 Limitations of the Study

This thesis is not free from limitations such as any other study. The study has several limitations. Firstly, it was conducted solely on Jordanian SMEs. The same research in another setting might generate different results since determinants could vary according to technological, organizational, political-environmental, and socio-cultural. However, one limitation is that the study was conducted in the private sector and lacked any opportunity to compare it with the public sector, such as government departments or agencies. Such studies could be directed towards broadening the research scale by collecting data from SMEs throughout Jordan, not from a specific city as Amman in this case. This will increase the generalizability of the findings. Another limitation is that all measurements were carried at a single point in time, and a study done at different times might revel varying results. Another limitation is that the response rate was comparatively low and the reason for this poor response rate has been explained in the methodology chapter.

This study used seven demographic profiles of owners/managers that could indirectly affect their perceptions and implementation of new technologies. It is proposed that future research include other demographic variables to identify if personal characteristics can shape what happens in the SME context, for example the role of one's social status, age of a SME and how this shaped its operations and structure, and more about employees' attitudes. This study did not employ a qualitative research approach. To further test the model, the researcher could have employed a qualitative approach to enrich our understanding of the factors affecting the acceptance of technological innovation. A study such as this could be extended to other industry settings, such as the manufacturing or services sector, which entails using a more extensive data set. Another limitation was evident in that there was no comparative analysis done of private and public sector organizations. Such a comparative study could enrich the analysis and findings of this research. Referring to practical constraints, this study was cross-sectional in that all measurements were taken simultaneously. A limitation, particularly for scholarly pursuits and publications, is the time period in which the measurements reported here were gathered. A more precise assessment, leading to a more robust conclusive basis for generalizations, is possible if such a study were conducted and measurements were taken over extended periods of time.

7.6 Future Directions for Research

Future research could try to incorporate more determinants that influence the perceptions of digital technologies. Furthermore, this thesis explored only one country, i.e. Jordan. It should be possible to conduct similar research in other Arab countries with relevant organizational settings of SMEs. A cross-cultural study on this topic will help us to better understand the perceptual differences that are evident in the Middle East countries. For example, the countries that make up the League of Arab States (LAS) would make an interesting point of comparison. Future analysis could incorporate more factors that affect individuals' perceptions and feelings about implementing digital technologies. The model developed for this study can be applied to a large number of technology adoption and managing problems. The conceptual model could be examined in other contexts or public sector agencies, given the ubiquity of digital technologies worldwide and which Jordan is increasingly influenced by.

Future research initiatives are suggested using a structural research model based on the tested hypotheses. Regression analysis was employed in this study to test the model created for this thesis. Regression analysis is one of the most extensively used approaches for testing a model. Utilizing a structural model in future research should be considered. Closely related to this, analyses in the future could employ structural equation modelling (SEM) or a covariance-based (CB) structural equation model to verify the indicator reliability of chosen measurement items. For instance, confirmatory factor analysis (CFA) may be used in research for the objectives above and more in-depth examination. A CFA might be employed if SEM methods are selected for future studies. Using partial least squares (PLS) is also possible. Finally, further research on this subject may include a test for heterogeneity in the dataset(s).

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Appendix 1: Participant Information Form

Project Title

Determinants of the adoption and impact of digital technologies in SMEs in Jordan.

Researcher
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Project Aim

This research investigates the adoption and impact of digital technologies in SMEs in Jordan. Although many studies have already been conducted on technology adoption in developed nations, only a few have been done on digital technologies in the Middle East (particularly in Jordan). Proposed here is a novel contribution that will address firstly, a significant gap in the literature by examining technological, organizational, socio-cultural, and political-environmental determinants on digital technologies adoption; secondly, the impact of digital technologies SMEs' quality and efficiency in the services they deliver. This study findings will help SMEs' decision-makers (generally owners/managers) make the best calls concerning digital technologies.

General Outline of the Project

This study aims to develop a theoretical model that incorporates technology adoption issues that cover technological, organizational, political-environmental and socio-cultural contexts. This study's combination of variables goes beyond previous research to bring together all the relevant determinants that may affect the perceptions and uses of digital technologies in SMEs' workplace settings. In Middle Eastern countries, social and religious values have long shaped and guided all employees' daily activities. This research explores the impact of social values on how digital technology adoption is perceived in the SME context. Notably, no study has to date addressed these determinants in Jordan. Therefore, this research will contribute to understanding the key determinants influencing the adoption of digital technology in Jordan and how it can economically and socially benefit that country's government and all sectors.

Participant Involvement

1. Please be advised that the individual responses to this study are strictly secure and confidential. Therefore, this study will not reveal the identity of those who have responded.

2. The survey questionnaire would take about 25 to 30 minutes to complete.

3. Please note that you are under no obligation to participate in this research because it is entirely voluntary.

4. Please be confident that all the data collected from participants will be stored securely and only accessed by the researcher. Excellent care will ensure that any data details do not identify individuals or their conditions.

5. Participation in the research is completely voluntary and participants may, without any penalty, decline to take part or withdraw at any time without providing an explanation or refuse to answer a question.

Benefits of Participation

You may benefit by participating in this research as the participants' managerial viewpoints woill enable other SME owners/managers to understand what digital technology adoption will mean to them. The chief inference is that owners/managers can make good and timely decisions regarding digital technologies. This research will accurately evaluate the potential improvements in the workplace environment, and the level of assistance and support required to consolidate businesses' needs and efficiencies.

Risks of Participation

The researcher avoids any physical risks of participation, including physical discomfort, the pain brought about by the research procedures or the emergence of issues such as anxiety, depression, guilt, shock and loss of self-esteem. The researcher will avoid all socio-economic risks, including loss of wages or other income and any other financial costs, such as damage to a subject's employability, due to participation in the research and avoid any legal risks.

Confidentiality

Only the researcher/s will have access to information provided by all participants. Privacy and confidentiality will be protected at all times. The research outcomes may be presented at conferences and written up for publication. However, in all these publications, the privacy and confidentiality of individuals will be protected, and no names will be published.

Anonymity

Please note that participants' answers to this study are confidential and secure. This study will not expose the identity of those who have responded to this study. Please be confident that all research details will contain no information that can identify any person.

Data Storage

The information collected will be stored securely on a password protected computer throughout the project and then stored at the University of Canberra for the stipulated five-year period after which it will be destroyed according to university protocols.

Future Research

If you agree, the information collected during the conduct of this study may be used in future research projects on related topics. Any future use of your data will comply with any conditions imposed by the Human Research Ethics Committee of the University of Canberra.

Ethics Committee Clearance

The project has been approved by the Human Research Ethics Committee of the University of Canberra (HREC – 11504).

Queries and Concerns

Queries or concerns regarding the research can be directed to the researcher and/or supervisor. Contact details are at the top of this form. If you have any complaints or reservations about the ethical conduct of this research, you may contact the University of Canberra's Research Ethics & Integrity Unit team via telephone 02 6206 3916 or email humanethicscommittee@canberra.edu.au or researchethicsandintegrity@canberra.edu.au

If you would like some guidance on the questions you could ask about your participation please refer to the Participants' Guide located at https://www.canberra.edu.au/research/graduate-research/current-research-students/integrity-and-ethics/ethics/accordion/human-ethics/human-ethics-documents/Agreeing-to-participate-in-research.pdf.

Appendix 2: Approved by Ethics Committee

27 April 2022

Dear Ra’Ed,

We are happy to advise that your Human Research Ethics Application is approved by the University of Canberra Human Research Ethics Committee.

Project ID: 11504
Project Title: Determinants of the adoption and impact of digital technologies in SMEs in Jordan.
Project Approved 21 April 2022 Project End Date: 3 September 2022
Investigators: Ra'ed Almashawreh, Dr Majharul Talukder, Dr Sarvjeet Kaur Chatrath.

The following general conditions apply to your approval. These requirements are determined by university policy and the National Statement on Ethical Conduct in Human Research (National Health and Medical Research Council, 2007).

Monitoring

You must provide the Committee with annual reports as well as a final report upon completion of the study. Please note: all amendments and any reviews must also be submitted to the Committee that granted original approval.

Reporting Adverse Events

You must report any unexpected adverse events or complications that occur anytime during the conduct of the research study or during the follow up period after the research. Please refer these matters promptly to the HREC. Failure to do so may result in the withdrawal of the Ethics approval.

Discontinuation of Research

You must inform the Committee, giving reasons, if the research is not conducted or is discontinued.

Extension of Approval

If your project will not be complete by the expiry date stated above, you must apply for extension of approval. This must be done before current approval expires.

Contact Details and Notification of Changes

You should advise the Committee of any change of address during or soon after the approval period including, if appropriate, email address(es).

Please do not hesitate to contact us via email humanethicscommittee@canberra.edu.au if you require any further information.

Kind regards,
Dr Matt Muskat
Research Ethics & Integrity Advisor
Research and Innovation Service

Appendix 3: Survey Questionnaire

Topic: Determinants of the adoption and impact of digital technologies in SMEs in Jordan.

(Note: Digital technologies indicated here refer to new and innovative computer-related systems chosen by SMEs in Jordan, for example Artificial intelligence (AI).

(A) Demographics (please tick the appropriate choice)

1. Your gender? (a) Male. (b) Female.

2. To which age group do you belong? (a) 20-29. (b) 30-39. (c) 40-49. (d) 50-59. (e) 60 and above

3. What is your highest academic qualification? (a) Primary. (b) HSC. (c) Bachelor. (d) Master’s degree. (e) PhD.

4. What is your employment experience? (a) 1-2 year (b) 2-3 year (c) 3-4 year (d) 4 -5year (e) 5 year or more.

5. **Which industry classification do you belong to?** (a) Construction and building materials (b) Automotive-related repair maintenance & trades (c) Wholesale and retail trades (non-automotive (d) Finance and insurance. (e) Food & beverages (f) Agriculture (g) Information, communication & technology (h) Tourism (i) Real estate (j) Other services.

6. **How many people does your business currently employ**? (a) None (b) 1-4 employees (c) 5-19 employees (d) 20-99 employees. (e)>99 employees.

7. What is your role in running the business? (a) Business owner (b) Director (c) Senior Manager (d) Manager (e) Supervisor

(B) Artificial intelligence (AI) Usage Level:

1. On average, how much time do you spend per week using AI for work?

(a) Less than 1 hour, (b) 1-2 hours, (c) 2-3 hours, (d) 3-4 hours, (e) More than 4 hours

2. On average, how frequently do you use AI in your work?

(a) less than once a month, (b) once a month, (c) a few times a month, (d) once a day, (e) several times a day.

3. Please indicate your level of usage of AI.

(a) not used at all, (b) used rarely, (c) used quite often, (d) used frequently, (e) used extensively.

4. How many different types of AI do you use?

(a) none, (b) 1-2, (c) 2-3, (d)3-4, (e) 5 and above

5. Do you use advanced features of AI?

(a) not used at all, (b) used rarely, (c) used quite often, (d) used frequently, (e) used extensively.

The questions below have answers scaled from one to five. Please tick mark (√) from the scale of 5, the most appropriately matching scale for your responses. Please indicate from 1 = Strongly Disagree (SD), 2 = Disagree (D), 3 = Neutral (N), 4 = Agree (A), 5 = Strongly Agree (SA).

(C) Independent Variables, Dependent Variables and Perceptions Variable:

Note: AI= Artificial Intelligence

Technology strategy	Strongly Disagree	Disagrees	Neutral	Agree	Strongly Agree
Our digital strategy accelerates new product and service launches.	1	2	3	4	5
Our digital strategy takes advantage of data, information, and knowledge.	1	2	3	4	5
Our digital strategy opens up entirely new chances to create value for our clients.	1	2	3	4	5
My company uses licensing agreements extensively regarding AI.	1	2	3	4	5
My company uses joint ventures for AI research and development.	1	2	3	4	5
Employees' IT Knowledge					

I gained knowledge from my previous work on how to use AI.	1	2	3	4	5
I learned from my prior training programs how to use AI.	1	2	3	4	5
I have learned to use AI in my previous job.	1	2	3	4	5
I learned from previous experience with similar new technology.	1	2	3	4	5
I am already familiar with a similar new technology system.	1	2	3	4	5
IT infrastructure					
IT infrastructure of my company is good.	1	2	3	4	5
IT infrastructure of my company can meet the business needs.	1	2	3	4	5
IT infrastructure of my company enable us to cooperate with all stakeholders.	1	2	3	4	5
IT infrastructure of my company is adequate.	1	2	3	4	5
IT infrastructure of my company can support all processes.	1	2	3	4	5
Managerial Support					
Management is aware of the benefits that can be attained with AI.	1	2	3	4	5
Management always encourages employees to use AI in their work.	1	2	3	4	5
Management is providing different types of support for AI adoption.	1	2	3	4	5
Management is keen to make sure that employees are using AI.	1	2	3	4	5
Management provides most of the essential help and resources to use AI.	1	2	3	4	5
Training					
My company provides training for employees to explain the features of AI.	1	2	3	4	5
My company is offering training sessions to improve AI usage.	1	2	3	4	5
My company is offering guidance for employees on how to use AI.	1	2	3	4	5
My company is offering specialized instructions regarding AI usage.	1	2	3	4	5

My company is offering a specific person for individualized assistance when employees face difficulties with using AI.	1	2	3	4	5
Reward System					
AI technologies assists me to save time in work.	1	2	3	4	5
AI applications assists me to accomplish tasks more quickly.	1	2	3	4	5
Using AI applications improves my productivity.	1	2	3	4	5
Using of AI applications keeps my private data more secure.	1	2	3	4	5
Using AI applications gives me to be flexibility in my work.	1	2	3	4	5
Government support					
Government encourages using AI applications.	1	2	3	4	5
Government facilities are available to use AI applications.	1	2	3	4	5
Government promotes AI applications	1	2	3	4	5
Government adopts an assertive policy to use AI applications.	1	2	3	4	5
Government support encourages firms to use AI in their business.	1	2	3	4	5
Government regulations					
Government establishes regulations in relation to AI usage.	1	2	3	4	5
Government regulations are significant for AI adoption.	1	2	3	4	5
Government policies encourage individuals to use AI applications.	1	2	3	4	5
The country's legal system supports the adoption of AI applications.	1	2	3	4	5
Government regulations help individuals to use AI applications.	1	2	3	4	5
Competitive pressure					
My company is under pressure from competitors to adopt AI.	1	2	3	4	5
Business competitors encourage us to implement AI applications.	1	2	3	4	5

My company would adopt AI in response to what competitors are doing.	1	2	3	4	5
AI would allow my company to have a stronger competitive advantage.	1	2	3	4	5
What competitors do will significantly impact our decision to use AI.	1	2	3	4	5
Peer Support					
I learned how to use AI effectively from my friends.	1	2	3	4	5
Communicating with my friends assists me to learn AI.	1	2	3	4	5
Opinions of people in informal groups to which I belong are significant to me regarding the use of AI.	1	2	3	4	5
Observing my friends performing similar tasks using AI increased my intention to use it.	1	2	3	4	5
People in informal groups to which I belong think using AI is valuable.	1	2	3	4	5
Social Network					
I use AI because my relevant organization also uses AI.	1	2	3	4	5
I use AI because my friends in another firm are using AI.	1	2	3	4	5
I use AI since other people use a similar system.	1	2	3	4	5
People in my discipline think that AI usage is valuable.	1	2	3	4	5
The opinion of people in my discipline is significant about AI	1	2	3	4	5
Religious beliefs					
My religion does not discourage the adoption of AI.	1	2	3	4	5
My religious opinion is optimistic about using AI.	1	2	3	4	5
My religion motivated me to use AI.	1	2	3	4	5
My religion gives me energy while using AI.	1	2	3	4	5
My religion enhances my caring for others and sharing knowledge about AI.	1	2	3	4	5
SME performance					

AI helps my company to perform much better than competitors about profitability as a percentage of sales.	1	2	3	4	5
AI helps company to perform much better than competitors for return on investment.	1	2	3	4	5
AI helps my company to perform much better than competitors concerning cash flow from operations.	1	2	3	4	5
AI helps my company to reach its financial goals.	1	2	3	4	5
AI helps my company to improve its brand visibility and reputation.	1	2	3	4	5
Productivity					
Using AI improves work motivation.	1	2	3	4	5
Using AI enables me to preform my tasks easier.	1	2	3	4	5
Using AI reduces the time I spent on unproductive activities.	1	2	3	4	5
Using AI increases the quality at my job output.	1	2	3	4	5
Using AI improves flexibility of my work.	1	2	3	4	5
Profitability					
AI helps my company to have good return on assets.	1	2	3	4	5
AI helps my company to have good return on investment.	1	2	3	4	5
AI helps my company to have good net income/revenues.	1	2	3	4	5
AI helps my company to have good return on equity.	1	2	3	4	5
AI helps my company to have good added economic value.	1	2	3	4	5
Customers' satisfaction					
AI helps my company to have close contact with customers.	1	2	3	4	5
AI allows my company to have good communication with customers.	1	2	3	4	5
AI assists my company to develop a good understanding of customers.	1	2	3	4	5
AI enables my company to build strong relationships with customers.	1	2	3	4	5

Our customers are more loyal to my company because of AI.	1	2	3	4	5
Market share					
AI assists my company to attain good market positioning.	1	2	3	4	5
AI helps us to be percentage share is higher.	1	2	3	4	5
AI assists my company to attract more customers.	1	2	3	4	5
AI assists us to be service efficiency is commendable.	1	2	3	4	5
AI assists my company to Alignment with market demands.	1	2	3	4	5
Sales Improvement					
The sales volume of our products has increased by using AI.	1	2	3	4	5
The prices of our products have changed after using AI applications.	1	2	3	4	5
The number of new customers that we are able to acquire has increased.	1	2	3	4	5
The number of existing customers that we are able to retain has increased	1	2	3	4	5
My firm sells more than its competitors after introducing AI.	1	2	3	4	5
Perceptions					
Using AI applications is important to your work.	1	2	3	4	5
Using AI applications is relevant to your work duties.	1	2	3	4	5
Using AI applications is helpful.	1	2	3	4	5
Using AI applications is practical.	1	2	3	4	5
I like the idea of using AI applications.	1	2	3	4	5

Please write your email address below if you wish to receive the results of this survey.
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