The Continued Usage of Artificial Intelligence in the United Arab Emirates Public Sector Organisations: An extended information system success model

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The Continued Usage of Artificial Intelligence in the United Arab Emirates Public Sector Organisations: An extended information system success model

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ABSTRACT

In the past years, government around the globe showed significant interest in Artificial Intelligence (AI) technologies, more governments are setting their AI related strategies and using Artificial Intelligence technologies separately or integrated with other technologies such as Internet of Things (IoT) or Big Data (BD) to enhance their citizens' offering, or increase the efficiency of their processes. Nevertheless, empirical research on what determines successful Artificial Intelligence (AI) usage and usage continuance in public settings remains scarce, especially regarding the impact of organisational constructs on the intention to continue usage of Artificial Intelligence in Public Sector Organisations in the United Arab Emirates. Therefore, this study was conducted to offer a better understanding of the impact of various organisational and technological factors on Intention to continue using Artificial Intelligence (AI) in organisations in the Public Sector in the United Arab Emirates.

This study tests the constructs identified from the updated Delone & McLean Information System Success Model (2013) and Technology-Organisation-Environment (T.O.E.) Framework and their impact on the successful usage and intention to continue usage of Artificial Intelligence in the Public Sector organisations in the United Arab Emirates. This was conducted through reviewing the existing literature in AI technologies and IS acceptance theories, which led to the introduction of a hybrid model from both the Delone & McLean Information Success Model (2013) and the Technology-Organisation-Environment Framework (TOE) with seven proposed constructs. A survey approach has been followed to collect primary data from 223 participants who use AI technologies in their respective federal and local public sector organisations. Structural Equation Modelling (SEM) has been used to test the conceptual model to measure the relationships impact significance of identified variables. The analysis of the data revealed that all seven constructs in the Delone & McLean Information Success Model and TOE framework hybrid model are accepted. The tested model showed moderate to high positive statistically significant correlations with intentions to continue usage of AI technologies. The results of the study revealed that Organisational Performance has a strong and positive significance impact on In Intentions to Continue Usage of AI technologies. In addition to that, analysis revealed that Organisational Culture and Digital Organisational Culture can be added to the model, as the results indicated that Organisational Culture has a strong and positive impact on Digital

Organisational Culture. Moreover, the study demonstrates the importance of culture in public sector. When comparing impact significance, the study showed that Actual Usage of AI systems is positively impacted by the two variables; System Quality and Digital Organisational Culture, nevertheless Digital Organisational Culture has greater positive impact than System Quality. Moreover, Organisational Culture and Data Management both have positive impact on System Quality and Digital Organisational Culture, but Organisational Culture has greater positive impact on System Quality and Digital Organisational Culture more than the positive impact of Data Management on System Quality and Digital Organisational Culture.

This study makes important theoretical contributions to both Delone & McLean Information Success Model (2013) and the Technology-Organisation-Environment Framework by providing a novel framework and model that integrates key concepts and mechanisms from both theories, which enables a more comprehensive and nuanced understanding of the research of interest. Specifically, the model developed in this study enhances our understanding of the complex interplay between various cognitive, affective, and behavioral factors that influence the outcomes predicted by these theories, and sheds new light on the underlying processes and mechanisms that drive these effects. Moreover, this research has several managerial contributions and implications, provides insights for Public Sector Organisations to understand the factors affecting AI systems usage success, which will help them in prioritizing and utilizing their resources more effectively. A new conceptual model was tested and validated which would help Directors, ICT specialists and programmers, and data scientists in identifying new ways to facilitate AI technologies adoption and usage. In addition, the study highlighted the importance of organisational culture in the usage of AI related technologies.

Thus, this research through the introduced model may enhance the ability of public sector organisations in the United Arab Emirates to better manage data, and the quality of the AI systems used, in addition to instilling a corporate culture and digital organisational culture that would enhance the actual usage of AI system which would enhance the organisational performance, and accordingly influence the organisation's intention decision to continue using AI technologies.

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LIST OF ABBREVIATIONS

ADP: Adaptability

ADM: Automated Decision Making

AI: Artificial Intelligence

AMOS: Analysis of Mean and Covariance Structures

AU: Actual Usage

AVE: Average Variance Extracted

BD: Big Data

BDAS: Big Data Algorithmic Systems

BOLD: Big Open and Linked Data

C.R.: Critical Ratio

CFA: Confirmatory Factor Analysis

CFI: Comparative Fit Index

CMIN/DF: Normed Chi Square

CON: Consistency

D&M: Delone & McLean

DM: Data Management

DOC: Digital Organizational Culture

DOI: Diffusion of Innovation

ICT: Information and Communications Technology

IFI: The Incremental Index of Fit

INV: Involvement

IoT: Internet of Things

IS: Information System

IT: Information Technology

ITCU: Intention to Continue Usage

MIS: Mission

OC: Organisational Culture

OP: Organisational Performance

PRE: Perceived Ease of Use

PRU: Perceived Usefulness

PSO: Public Sector Organisations

RBT: Resource-Based Theory

RBV: Resource-Based View

RMSEA: Root Mean Square Error of Approximation

SEM: Structural Equation Modelling

SQ: System Quality

TAM: Technology Acceptance Model

TEF: Technology Enactment Framework

TLI: Tucker-Lewis Index

TPB: Theory of Planned Behaviour

TRA: Theory of Reasoned Action

UAE: United Arab Emirates

DECLARATION

I declare that the work contained in this thesis has not been submitted for any other award and that it is all my own work. I also confirm that this work fully acknowledges opinions, ideas and contributions from the work of others.

Any ethical clearance for the research presented in this commentary has been approved. Approval has been sought and granted through the Researcher's submission to Northumbria University's Ethics Online System on **01 February 2021 – submission Ref. 28647.**

I declare that the Word Count of this Thesis is words: 52,164

Name: FARES MOKBEL DAHABREH

Date: 17/03/2023

DEDICATION

I dedicate this thesis to

Mokbel Dahabreh & Muntaha Qatami

My late father, you always live in my heart and mind.

My mother, your kind heart and wise words are always there for me

You helped find my path, taught me how to face life, and become the man that I am now.

Tala Qubain

My wife and partner

You were the best companion in such a journey, without your support, patience, smiles, and sacrifice nothing could have been done!

Love you

My precious Tia F. Dahabreh & Laith F. Dahabreh

You are my source of pride and happiness, you fill my life with joy and love

Tala, Tia and Laith gave a new meaning to life with a purpose

This work is dedicated to them …

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PUBLICATIONS

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CHAPTER ONE: INTRODUCTION

1.1 INTRODUCTION:

This introductory chapter presents the DBA thesis titled: "*The Continued Usage of Artificial Intelligence in the United Arab Emirates Public Sector Organisations: An extended information system success model.*" In the following sections, background and drivers for this research are presented, then the research questions and objectives, followed by an illustration of the research process and then the philosophical and methodological choices made, and finally the outline of the thesis is presented.

1.2 RESEARCH BACKGROUND:

The world is facing advancements and breakthrough in technologies that will transform how the individuals live and work, and even how organisations' business models operate, and one of those revolutionary technologies is Artificial Intelligence (AI) (Zaki, 2019; Periera *et al.*, 2023). In the recent years, organisations in different sectors have been adopting AI, which is reshaping how business is being done, how decisions are made, and how organisations are communicating internally and with their external stakeholders. Similar to organisations in other sectors, government entities are showing increasingly interest in adopting AI related technologies. This research is concerned with identifying practices to enable Public Sector entities in the United Arab Emirates continue using Artificial Intelligence (AI) related technologies successfully.

Artificial intelligence's roots can be traced in studies and literature to the 1940s, then went through ups and downs (Haenlien & Kaplan, 2019) until recent years, where several trends and changes in the business industry emerged, e.g. smart government initiatives, the fourth industrial revolution, automation, Big Data (BD), the Internet of Things (IoT), the power of computing and information systems, and many other trends, that reshaped both private and public sector organisations.

One of the fields that was directly affected by those trends and changes was Information Systems (IS), and Artificial Intelligence in specific. This was due to rapid advancement in technologies and disciplines that enable AI, e.g. platforms, databases, internet technologies, and data science, which are becoming more affordable and more accessible (Fountaine *et al.*, 2019).

The Artificial Intelligence (AI) industry is emerging as a critical component of the technology industry. The AI integration required access towards the properties and objects within the settings to develop judgmental realities between the provided information. AI primarily relies on the cores of machine learning, and with these cores, it mimics human intelligence (Zhang & Lu, 2021). The implications of AI are divided into three major segments; ANI, the type of AI responsible for performing a single task with intelligence and smartness, falls in this category like the Voice Assistant; AGI, often used for general tasks and the efficacy of this type of AI is not restricted to any single task as in the case of AlphaGO; ASI, the most potent type of AI system possessed the capacity of Cognition (Di Vaio *et al.,* 2020). All of the concerned types of AI are applied in the practical sector for developing advanced organisational systems.

The importance of AI in the practical dimension is gaining interest among all the business, industrial and services sectors across the globe, in addition to public sector. It was highlighted that primarily the AI allowed enhanced management on multiple organisational levels, which allowed the task management and administration of the daily tasks without any interventions of the human workforce. The implications of AI practically automated the processes that critically appeared as one of the primary importance of AI in reasonable prospects (Alam *et al.,* 2022). Additionally, the implementation of AI allowed for enhanced analysis of complex problems that served as the foundation of developing a practical recommendation for better outlays of the results and organisational objectives; in this manner, the technology of AI appeared as the time-saving and capacity or productivity-enhancing factors on different practical implementations (Lee & Yoon, 2021). The programming of the AI is the actual supercomputer because the programmed codes identify the project or work cores and address them in the best possible manner with adequate speed, critically inducing some key benefits.

Furthermore, cost-saving and financial efficiency are vital at every organisational level and equally important in every sector. The implementation enhanced the overall accuracy and the planning of the processes via the channel of practical and real-time data visualization; this visualization of the data allowed the targeted monitoring of the process or project flow that conclusively elevated the level of brainstorming and collective decision-making processes (Duan *et al.,* 2019). Additionally, team management is another crucial benefit that excessively developed the importance of AI; by the channel of AI, it is possible to achieve effective task prioritization that eliminates the element of team working complications (Akata *et al.*, 2020). Hence, it was evident that the practical implication of AI possessed some significant benefits and importance that guided the direction of many future research studies towards this particular research topic.

Artificial Intelligence (AI) holds significant potential to contribute to the success of public sector organisations due to the wide impact of AI applications on organisational processes, communication channels, products and services delivered, and enhancing the decision-making processes (Marr & Ward, 2019), in addition to improving the customer experience and voice of customer approaches (Zaki *et al.*, 2021), and thus the value offered to citizens and stakeholders. Nevertheless, organisations adopting AI face several challenges that may lead to failure or poor results, and therefore there has been a growing need for research on factors / practices influencing successful adoption and usage of AI and its applications (Santeli & Gerdon, 2019).

Many countries in the world are turning into AI, and one of them is United Arab Emirates (UAE), which is investing in new AI-based technologies to shape the future of its government and enhance services provided. The UAE was the first country in the world to appoint a Minister for Artificial Intelligence affairs, and was one of the pioneering countries to introduce a vision for AI; as the country's leadership announced and launched the "UAE Strategy for Artificial Intelligence" in October 2017, covering nine targeted sectors e.g. transport, health, technology, education, and others, therefore many public sector organisations in the UAE have already started implementing with some of its applications, or are planning on to adopt AI or are continuing to use AI (Halaweh, 2018).

The literature review showed that there are many studies on AI as a topic in general, in addition to an increasing research interest in covering different aspects of AI including; identifying AI maturity levels, opportunities for organisations, its applications and challenges of adopting AI in the public sector, nevertheless, there is a lack of empirical studies conducted to identify the factors needed to successfully adopt, use, and continue using AI in public sector organisations, and guide them through their transformation journey to implement AI, and achieve the desired outcomes.

This research aims to identify and test the organisational dependent and independent constructs in a hybrid model integrated from the updated version of Delone & Mclean IS Success Model (Petter *et al.*, 2013) and Technology-Organisation–Environment Framework that will enable Public Sector Organisations in the UAE successfully use and continue using AI. This will pave the way and assist interested public sector entities plan and implement AI successfully, and overcome the challenges and the different organisational and cultural barriers they might face (Fountaine *et al.*, 2019).

1.3 RESEARCH QUESTION AND OBJECTIVES:

The aim of this research is to examine an organisational Artificial Intelligence usage Model based on testing and explaining the variables in a hybrid model between the updated Delone & Mclean Information Success Model (2013) and Technology-Organisation-Environment Framework (T.O.E.) that would enable public sector organisations in the United Arab Emirates use and continue using Artificial Intelligence related technologies successfully.

1.3.1 Research Question:

The research question in this study is:

What is the impact of organisational constructs on the intention to continue usage of Artificial Intelligence in Public Sector Organisations in the United Arab Emirates?

1.3.2 Research Objectives:

The purpose of this research is to examine the factors affecting the AI technologies usage continuance intentions in public sector organisations in the United Arab Emirates. The three research objectives are:

1. Identify organisationally suitable technology adoption model(s) with relevant constructs based on existing literature.
2. Develop a conceptual model for the organisational intention to Artificial Intelligence technologies usage continuance in the public sector organisations in the United Arab Emirates.
3. Test the validity of the conceptual model in the context of public sector organisations in the United Arab Emirates.

1.4 SIGNIFICANCE OF THIS STUDY

This study is targeting the public sector to test the proposed conceptual model. In general, the public sector appeared very complex in contrast to other sectors such as the private sector. The adoption and usage of AI related technologies is referred to as innovation. Mostly, innovation in the public sector is often confined towards the induction of new processes and positioning of new products or services, even sometimes leading towards the inclusion of an entirely new paradigm, neglecting the prospect of enhancing the organisational performances with the improvement of existing organisational layout which was the actual motive of AI induction on an organisational level (Chen *et al.*, 2020). Despite the evidence suggesting that the inclusion of AI technologies in the public sector created enhanced societal value along with increasing the efficiency of the overall processes, it included better alignment with the needs of the people (Neumann *et al.*, 2022).

In a similar direction, it was revealed that IS innovation is comparatively complex among the other innovations in the general-purpose technology quadrants, which typically differentiated this innovation but at the same time made this innovation typically tricky to handle on a significant public organisational level while in contrast to other technologies that very easy and effectively deployed in the public sectors; utilization of Social Media. This complexity of the AI adoption made its integration between the IT units and the AI experts with the other organisational level that is also a challenging prospect on a sizeable public sector level (Jöhnk *et al.*, 2021); hence the overall complexity of the AI adoption and usage is indicated.

Moreover, Berryhill *et al.* (2019), illustrated that the government could effectively utilize the AI technologies and tools for designing better policies and decision-making with accurate time alignment with the public interest based on data analysis and predictive analytics features. Additionally, the inclusion of AI innovation enhanced the communication and engagement of the citizen with government bodies through technologies like Chatbots; conclusively quality and speed of public services became rapid and penetrating. However, added to this, Campion *et al.* (2020), made the fact profound that AI possessed various benefits on the general sectorial level. However, attaining these benefits is a very complex task that requires strategic and theoretical support. Wirtz *et al.* (2021), discussed another dimension where the major problem that government bodies faced while adopting AI was associated with the prospect of mimicking the AI integration of the private sector; however, that steep learning culture with a specific purpose catered for the complexity of AI adoption, but the government entities possessed a unique culture and have to face a variety of different environmental challenges.

However, some governments across the globe cracked the code of effective AI usage in the public sector, and some of the top nations like the USA, the UK and the UAE effectively utilize AI on the public level. The USA utilizes Artificial Intelligence in the most sensitive government body, the Department of Defense (DOD). The AI tools incorporated with the DOD automated simple, time-consuming tasks like financial data processing. Additionally, AI was used to predict and detect mechanical failures in weapon development and testing. This complex analysis was performed accurately with AI-enhanced warfare focus on the USA (Board, 2019). Moreover, in the region of the UK, the public sector is significantly inclined over the data sciences and utilization of AI either for policy development or service delivery system. On the Government level, UK public sector industry developed the synergy that adequate and enhanced implementation of AI could only be possible with cross-level collaboration, under which there was a rise in the collaboration between the technology universities, and the public sector of the UK to support the adoption of AI (Mikhaylov *et al.,* 2018).

From the standpoint of the UAE government, the public sector enhanced the communication and interaction between the citizens and the government officials under which the facility of AI-enabled Chatbots or Virtual Assistants became incorporated in almost every public sector organisation of the UAE, which enhanced the interaction virtually (Makasi *et al.*, 2021).

Thus, all of the information mentioned above critically established the fact that AI possesses strong potential at the public sector level, and many top governments across the globe effectively use AI integration in public organisations; however, the usage of AI related technologies at the public sector level is a complex task that possessed room for further research and development for better adoption, which critically established the significance of this vital research study.

1.5 DEFINITIONS AND ASSUMPTIONS

1.5.1 Definitions:

Based on the literature review conducted, the study included seven main concepts: data management, organisational culture, digital organisational culture, system quality, actual usage, organisational performance, and intention to continue usage. Table (1-1) summarises the main constructs adopted in this research and their definitions.

Table 1- 1: Definitions of Main Constructs

Construct	Definitions	Source
Data Management (DM)	*"A group of activities relating to the planning, development, implementation, and administration of systems for the acquisition, storage, security, retrieval, dissemination, archiving and disposal of data"*	(Office of the Deputy Prime Minister, 2005)
Organisational Culture (OC)	*"Set of beliefs, values, and assumptions that are shared by members of an organisation, thus, it helps define what is important to the organisation and directs all stakeholders towards achieving these important goals."*	(Barney, 1986; Kerr & Slocum, 2005)
System Quality (SQ)	*"Desirable characteristics of an Information System (IS), and can be measured by different measured such as ease of use."*	Petter *et al.* 2013; Delone & McLean 2003)
Digital Organisational Culture (DOC)	*"A set of shared assumptions and understanding about organisation functioning in a digital context."*	(Deshpande & Webster's, 1989; Martínez-Caro *et al.*, 2020)
Actual Usage (AU)	*"Degree and manner in which staff and customers utilize the capabilities of an Information System (IS), and some examples of the measured used for use of Information System; amount of use, frequency of use, nature of use, extent of use."*	(Petter *et al.* 2013; Delone & McLean 2003)
Organisational Performance (OP)	*"The organisation's ability to attain its goals or achieve its goals and objectives by using resources in an efficient and effective manner."*	(Daft, 2000); Richardo & Wade, 2001)
Intention to Continue Usage (ITCU)	*"The persistent use of an ICT beyond its first use, that is, the continuous employment of a technology on a regular basis. It refers to expected future consumption or usage of an ICT and are closely related with actual usage."*	(Hernandez-Ortega *et al.*, 2014; Bhattacherjee, A., 2001)

1.5.2 Assumptions:

This study makes the several major assumptions listed below:

1- The Constructs identified in this research are measurable through perceptions of leaders and employees in targeted organizations.

2- All public sector organisations in the United Arab Emirates are subject to following the UAE national AI Strategy 2031.

3- Each Public Sector Organisation has its own distinguishable set of organisational culture.

4- Each Public Sector Organization is using at least one Artificial Intelligence related technologies system in one of its functions or units.

1.6 RESEARCH PROCESS:

This research followed an interactive process in order to answer the research question and meet the set research objectives (Newman, 2014). This process consisted of the main phases depicted in Figure (1-1) below, which seem to be sequential, yet steps blend into each other as the outputs or findings of a step may stimulate changes or actions in previous ones (Newman, 2014; Saunders *et al.*, 2019).

Figure 1-1: Main Research Process phases from (Newman; 2014, p. 25)

1.7 RESEARCH PHILOSOPHICAL AND METHODOLOGICAL CHOICES:

Artificial Intelligence falls under Information System/Information Technology (IS/IT) family, and when conducting a research in Information System fields, studies have shown that there are several philosophical positions that can be adopted in the IS/IT research

(Mackenzie & Knipe, 2006; Goldkuhl, 2012) such as Positivism, Interpretivism, and Pragmatisim.

There are factors affecting adoption of philosophical stances in researches (Tashakori & Teddlie, 2009; Bryman, 2008) such as:

1. Reasoning applied to data (inductive vs. deductive).
2. Role of the researcher (subjective vs. objective)
3. Nature of the research questions, and research contents.

Taking all the factors and bases mentioned above, the philosophical stance that will be followed in this research is **Positivism**, and a deductive approach is followed to quantitatively test through a survey with the identified variables in organisations that already started adopting AI and then extending the Delone & Mclean Information System Success Model (2003) into a hybrid model with Technology-Organisation-Environment Framework from AI perspective in organisational context.

The AI organisational digital transformation journey requires entities to implement examined practices to enable them shift from their current state to enter the AI and digital era, overcome challenges and eliminate failure. This researcher is conducting this research on the following bases:

1. The selected IS adoption theory constructs will be used to build a conceptual model then the hypotheses are developed.
2. The hypotheses are tested through a survey filled by public sector organisations in the UAE based on their own experience and actual implementation.
3. The role of the researcher is to collect and analyze data objectively without any personal influence on participating organisations or interpretation of results.

The researcher customized the research 'onion' as proposed by Saunders *et al.* (2019), to portray the philosophical and methodological choices taken for this research.

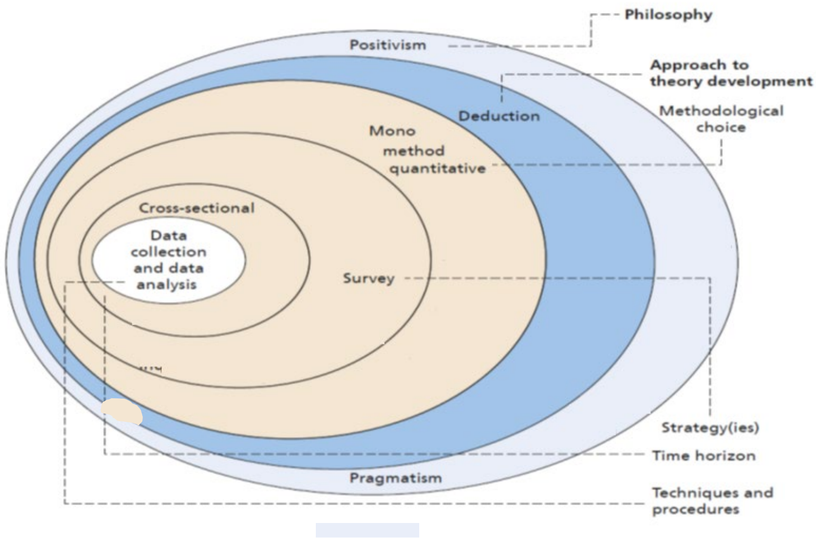

Figure 1-2: The research 'Onion' (Saunders, *et al.*, 2019)

1.8 CHAPTERS OUTLINE

Within this section, the chapters' outline of will be explained briefly. This thesis is structured of eight chapters with relevant appendices. *Chapter 1,* is an introduction and describes the background and drivers behind this thesis, in addition it clearly states the research question and the set objectives, illustrates the significance of the study, in addition to defining the main concepts and assumptions, as well as presenting the main research process followed.

Chapter 2, reviews the relevant literature from peer-reviewed highly ranked journals. It presents the background of Artificial Intelligence, definition adopted in this research, the challenges, and relation with other technologies, the adoption of AI in public sector in general and in the United Arab Emirates in specific. Furthermore, several Information System / technology adoption theories were presented and the justification of the chosen framework is discussed, in addition to outlining the identified research gap and knowledge contribution.

Chapter 3 includes the developed theoretical framework. This includes the selection of the various constructs identified in the literature reviewed in this research. This chapter concludes with clear visual relationship presentation of the final research theoretical framework.

In *chapter 4*, describes the proposed quantitative methodology clearly. Each methodological choice taken is presented with a clear reasoning behind the decision, including the research methodology and the research strategy. Another aspect is presenting the data collection and sampling techniques used to answer the research question and objectives.

Chapter five presents the conceptual model proposed in this study. Drawing on the conducted literature review and theoretical framework, and the identified set of constructs this model proposes eight hypotheses to testing and analyzing the significance of the impact of the htpothesised relationship. Moreover, this chapter discussed the operationlisation of the variables.

Chapter six outlines the quantitative analysis of collected data, and tests conducted on proposed conceptual model. This chapters includes the main steps followed to administer the online questionnaire, reports results via statistical descriptive and Structural Equation Modeling (SEM) analyses, and tests the hypotheses and reports significance levels.

Chapter seven presents the main findings of data analysis results in chapters six, and discusses the model proposed hypotheses perspective. It discusses the results of testing the eight hypotheses regarding the impact significance of relationships between the latent constructs in the structural model.

Last Chapter, *Chapter eight* briefly summarises the high-level results and conclusions of the thesis, presents research's contributions and implications from the theoretical and managerial perspectives, discusses the limitations of the study, and makes forwards recommendations for future research opportunities.

1.9 CONCLUSIONS

This chapter gave an overview of research subject, presented the research question and objectives, and highlighted the main research process activities, and provided an outline of the thesis as a whole. The next chapter is a review of existing literature in relation to AI, in addition to technology adoption theories.

CHAPTER TWO: LITERATURE REVIEW

2.1 INTRODUCTION

This chapter covers the literature review on the usage and intention to continue usage of artificial intelligence in the Public Sector in the United Arab Emirates. Technology in general is not new to the public sector; yet, the usage of AI and its related technologies in governments is still nascent (Valle-Cruz *et al.*, 2020; Sun & Medaglia, 2019).

The literature review in this study targeted AI related articles published between the years 2010 – 2023, with a focus on AI in public sector or government and excluding fully technical AI articles. First section is an introduction to the chapter, followed by section two with a review of the literature covering background of Artificial Intelligence (AI) and its history, the AI definition, AI different technologies, then the adoption of AI in the public section, followed by a brief on smart government, AI and other technologies, and then the main challenges facing AI and the different perspectives discussed in literature. Then review on ethical AI issues, which is followed by the adoption of AI in the public sector in the United Arab Emirates Section. A review of literature on data management and digital organizational culture, selected Information Systems (IS) technology adoption theories are discussed and evaluated.

Section three highlights the previous research and the knowledge gap, then section four discussing originality of research and contribution, while section five covers the conclusions based on literature review.

2.2 REVIEW OF THE LITERATURE

2.2.1 Background of Artificial Intelligence

Artificial intelligence is not a new term or concept, and since its introduction, AI has gone through three main stages. First, the Inception: *Isaac Asimov* firstly introduced the concept of Artificial Intelligence in the 40s of the twentieth century in the short science fiction story "*Runaround",* which inspired back then scholars, in addition to the future generations' scientists working in the fields of AI, robotics and computer science. This story explicitly featured three laws of robots that govern the relationship between humans and robots, and how a robot was to follow those laws (Haenlein & Kaplan, 2019), then secondly, in the early 50s, Alan Turing published his article "*Computing Machinery and Intelligence*", which covered the topic of developing intelligent machines, with a special focus on testing their intelligence. This test, which is known as "Turing Test", is still regarded until today as the reference point or benchmark for identifying intelligence of artificial system(s).

Third stage was more related to the origination of the term Artificial Intelligence in 1956. Dartmouth College in New Hampshire launched the Dartmouth Summer Research Project on Artificial Intelligence (DSRPAI), which was hosted by Marvin Minsky and John McCarthy, after which "artificial intelligence" has been coined to describe technologies with features and abilities that greatly resemble human intelligence (Gesk & Leyer, 2022; Galloway & Swiatek, 2018).

In the following years, the focus on Artificial Intelligence as a field went through several ups and downs / vicissitude focus eras, but during the past decade, the notion of Artificial Intelligence has come back strongly to the surface.

2.2.2 Definition of Artificial Intelligence (AI)

In general, researchers consider Artificial Intelligence (AI), as a term, as an "Umbrella term" due to its nature. AI encompasses different technologies, covers a broad scope of technologies such as Machine Learning (ML), Deep Learning (DL) and others technologies that are discussed later in this chapter. Hitherto, a universally accepted definition of AI remains elusive (Mikalef & Gupta, 2021; Wang, 2019; Wirtz, 2019; Grosz *et al.*, 2016), so far, there is no universally accepted unified definition and no consensus by scientists, researchers, developers and practitioners on its definition (Kuziemski & Misuraca, 2020).

Literature showed that the definition of Artificial Intelligence has altered and evolved over time from considering it as science and machines with a focus on programs, as defined by McCarthy *et al.* (2006): "Science *and engineering of making intelligent machines, especially intelligent computer programs"* to definitions which perceive AI as a system and set of functions that interact with external surroundings and interpret collected data such as the definition by Haenlein & Kaplan (2019): "*A system's ability to interpret external data* *correctly, to learn from such data, and to use those learnings to achieve specific goals and tasks through flexible adaptation"*.

Nilson (2010), from another perspective, considered AI as an activity that also interacts with its environment as set in his definition "*Artificial intelligence is that activity devoted to making machines intelligent, and intelligence is that quality that enables an entity to function appropriately and with foresight in its environment"*.

Other researchers considered AI as part of other systems, for example, Kuziemski & Misuraca (2020) adopted a definition for artificial intelligence that is in line with what is proposed by the European Commission (2018), which will be discussed below, but at the same time, they considered that the terms artificial intelligence and automated-decision making (ADM) are used interchangeably. Madan & Ashok, (2022) looked at AI as part of Cognitive Computing Systems (CCS) in their definition of AI "*a cluster of digital technologies that enable machines to learn and solve cognitive problems autonomously without human intervention*", similarly, Desouza *et al.* (2020) recognized the cognitive abilities of AI systems, which differentiate them from other systems. In general, CCS have the following five characteristics:

1- Ability to learn from multiple sources; data and human interactions
2- Ability to draw on characteristics of surrounding environment (context-sensitive), e.g. users' profile
3- Ability to recall history, e.g. historical data, and previous interactions
4- Ability to interact with Humans through Natural Language Processing (NLP)
5- Ability to provide actionable weighted recommendations

Despite all the efforts to define AI by researchers, Dwivedi *et al.* (2019) argue that what is in common between different AI definitions is their agreement on the capabilities of machines to perform tasks currently executed by humans. At the same time, it has been noted that the definition of AI varies depending on the purpose of the project(s) or functionality of AI application(s), Dwivedi *et al.* (2021) views defining AI presents terminological challenges, and suggest an "institutional hybrid" approach to defining AI and its typology as per the context and discipline of use.

Wang (2019) discussed the issue of defining "Artificial Intelligence", and started with defining the term "definition", then classified definitions into two types; a dictionary definition (descriptive), and a working definition (prescriptive) whose quality as a definition is measured against the degree it satisfies the following requirements; to what degree the definition matches what is explained about it, how exact the definition is, how fruitful the definition is, and lastly, how simple the definition is.

Wang (2019) argued that working definition of AI should not be judged as correct or not, but at the same time, not all working definitions are considered *"equally good"*, because it is the researcher who should choose an appropriate use for the term "AI" depending on the context of use, therefore, it is not mandatory to have a clear set definition for a concept to be used in research or discussions, nevertheless it is highly desired.

Pereira *et al.* (2023) considered AI as a technology that gives computers the ability to autonomously gather and interpret information from their surrounding environment for the purpose of making decisions, solving issues, and carrying out other actions which require human reasoning, AI aims to make machines think like people while outperforming the way humans function (Periera *et al.*, 2023). Based on what has been mentioned above, this study followed in this thesis the definition adopted by the European Commission (2018): *"Systems that display intelligent behavior by analyzing their environment and taking actions – with some degree of autonomy – to achieve specific goals"*. This definition was adopted as a working definition because it perceives AI as a system (computing system) that interacts with the surrounding environment, and at the same time takes action to accomplish or achieve a goal, which suits the functions of public sector organizations.

2.2.3 Artificial Intelligence Technologies

Artificial Intelligence can be looked at from different perspectives; technology vs. domain utilization. Firstly, from technology perspective, and as previously discussed, AI development got a boost in the 21st century due to several factors such as the advancement in data science and technology, and in computational power (Haenlein & Kaplan, 2019; Desouza *et al.*, 2020) which resulted in new programming languages, advanced forms of multiple algorithms and data science.

Those factors have led to the introduction of more complicated AI technologies, some of which are presented in Figure (2-1) AI related technologies / typologies (Ma *et al.*, 2018; Kuziemski & Misuraca, 2020; Noordt & Misuraca, 2022).

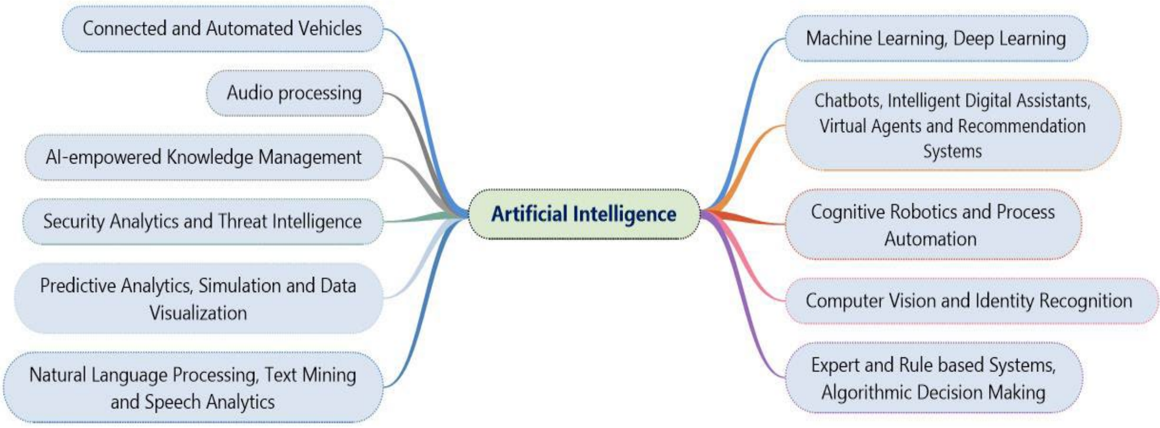

Figure 2-1: AI related technologies / typologies

The second perspective is the domain utilization. AI can be classified based on its domain utilization into 'weak' or 'narrow' AI, or 'strong', 'general' or 'super' AI (Naudé & Dimitri, 2020; Narain *et al.* 2019). The difference between weak AI and strong AGI is in the learning capabilities and scope of domain, as weak AI is utilizing 'deep learning' technology to learn more from large volume(s) of data about a specific domain and cannot be transferred to other domains, whereas strong AI is a general purpose technology that can be applied to all problem solving as it is true intelligence that is similar to human intelligence, and on the contrary to weak AI, it is not limited to a specific task or domain.

It is worth to mention that artificial super intelligence/AGI does not exist so far, but with the advancement in computer and data sciences, and in bio engineering the breakthrough in AGI will occur in the not-so-far future, which is expected to follow a simplistic S-shaped curve for technology diffusion – slow introduction, then rapid growth followed by full takeover of the markets, or a hostile strategy (Naudé & Dimitri, 2019), therefore, Narain *et al.* (2019) argue that there is a pressing need to steer the development of an artificial general (or super) intelligence, which has potential benefits, but at the same time threats to the humans.

Additionally, to avoid the dangers of an unfriendly or threatening AGI, governments need to influence the AGI related research and race through controlling what AGI/ASI can do, and what ASI wants to do. There are some proposed initiatives that can assist in influencing AGI (Naudé & Dimitri, 2019; Narain *et al.*, 2019), such as:

- Compensation and Rewards initiatives
- Enabling more public control through taxing AI and calibration of taxes to be low for friendly AGI and higher rates for unfriendly models.
- Enabling public procurement, which is valuable in helping to guide AGI towards a friendly path by regulating AI and mandating requirements and constraints, if needed.
- Addressing AI patency issues, through amending the relevant laws and regulations to reduce the risks associated from the AGI race.
- The management of artificial superintelligence from both evolutionary and control aspects.

A study conducted by Margetts & Dorobantu (2019) proposed that governments should adopt and try Artificial Intelligence to enhance the provision of services, consisting of three major tasks: detection, prediction and forecasting future needs, as well as simulation. Additionally, public servants are utilizing artificial intelligence to assist them in social services and welfare payments, determining immigration status, fraud detection, new infrastructure projects planning, communicating with citizens and answering their enquiries, determining healthcare priorities, and setting paths for drones.

Wirtz *et al.* (2019) summarized the main AI applications in addition to their relevant value creation and functional proposition in the (Table 2-1) below.

Table 2-1: AI applications and their relevant values (Wirtz *et al.*, 2019)

AI Application	Added Value	Public Sector Use	Source
AI-Based Knowledge Management Software	Knowledge generation and systematization	AI powered Clinical documentation	Lin *et al.,* 2018
	Knowledge codification		
	Knowledge analysis, distribution and sharing		
AI Process Automation Systems	Standard Tasks automation	Processing immigration requests in faster and higher quality Automated diagnosis of images Human-Computer interaction for repetitive tasks	Chun, 2007; Collier *et al.,* 2017; Jefferies, 2016
	Complex human action processes		
	Workflow processing, schematics based suggestions, data mining and others		
	Mimic human interaction with user interfaces of systems e.g. Robotic Process Automation (RPA)		
Virtual Agents	Interactions through speech analytics, computer vision, written data	Smart HR services, virtual nursing assistant, Refugees assistance Chabot	Zheng *et al.,* 2018; Collier *et al.,* 2017; Mehr, 2017
	Perform tasks for humans		
	Avatars and Chatbots		
Predictive Analytics & Data Visualization	Data Analysis	Police monitoring and prevention activities, threats and risks determination, Water levels prediction	Power, 2016; Kouziokas, 2017; Kouzokas *et al.,* 2017
	Big Data processing and analysis		
	Algorithm learning		
Identify Analytics	Integration between different advanced technologies to perform advanced analytics and identify access management	Criminals face recognition, Fraud detection and data security	Power, 2016; Hemken & Gray, 2016
Cognitive Robotics & Autonomous Systems	Learn and respond to surrounding environment	Electric-powered autonomous vehicle for public transport, Robot assisted surgery	Christchurch Int'l Airport Ltd., 2016; Jefferies, 2016; Collier *et al.,* 2017
	Determine and adapt human behaviour		
Recommendation System	System to filter information	Provide personalized information to public sector employees	Cortes-Cediel *et al.,* 2017
	System to personalize information and predict preferences		
Intelligent Digital Assistants (IDA)	Speech analytics	Connecting governmental programs IDA-Amelia (speech analytics and affective computing)	Herman, 2017; Jefferies, 2016
	Search for information or complete simple tasks		
Cognitive Security Analytics & Threat Intelligence	Analyze security information	Watson for Cybersecurity	Dheap, 2017
	Information interpretation and organizations		
Speech Analytics	Natural language processing and intelligent recognition	Real-time speech and text in face-to-face events translation Administrative workflow assistance (Voice to text transcription)	Microsoft, 2018; Collier *et al.,* 2017; Pannu, 2015
	Understand natural language, translate from spoken to written or respond to natural language		
	Real-time universal translation		

Lastly, in 2022, OpenAI and other firms released a machine learning chatbot called ChatGPT that uses Large Language Model (LLM). Currently, ChactGPT is capable of convincingly conversing with potential users in English and other languages across a vast series of topics through learning autonomously from data and training on a large volumes of data set of text to produce seemingly intelligent and sophisticated writing, for example programmers used this technology to write computer codes, researchers utilized it to produce literature through writing essays, summarizing existing literature, or even preparing draft papers, as well as identifying research gaps (Van Dis *et al.*, 2023).

2.2.4 Artificial Intelligence in Public Sector (PS)

During the past years, there has been a rise in the variety of AI applications due to recent developments in Artificial Intelligence and its related technologies, increased processing and computational powers, and the widespread datafication of societies, which led to the increased availability of large volumes of data (Noordt & Misuraca, 2022). Public Sector is considered as a suitable context to use AI related technology, that is because of its constantly changing environment which does not suit the preprogrammed technologies, opposite to AI technology does not make decisions on preprogrammed if-then logic (Medaglia *et al.*, 2023), therefore, AI implementation in government and public administration is gaining momentum (Madan & Ashok, 2022), and rapidly growing in the public sector (Gesk & Leyer, 2022), which was reflected in governments increased exploring and investing in Artificial Intelligence and its related technologies to enhance their public services (Andrews, 2022; Noordt & Misuraca, 2022). Zhang *et al.* (2021) considered Artificial Intelligence technologies as digital innovations that have the potential to fundamentally change the public sector, and many countries such as United States of America, China, France, Germany and Canada, to name a few, perceived AI as a revolutionary technology, and thus followed a vision that promoted AI as a strategic direction to ensure their future prosperity (Lepage-Richer & Mckelvey, 2022).

The implementation of technologies in government organizations is not new, nevertheless the adoption of Artificial Intelligence and its technologies in this sector is still nascent (Valle-Cruz *et al.*, 2020; Sun & Medaglia, 2019), nonetheless, there is an increase interest in AI in the public sector to enhance efficiency and create value for citizens (Mikhaylov *et al.*, 2018). Therefore, the public sector can use the suitable AI technology(ies) and benefit greatly through the technologies' abilities to enhance customers' experience (Zaki *et al.*, 2021), in addition to innovatively augment and improve organizational performance in the following areas (Mikhaylov *et al.*, 2018; Valle-Cruz *et al.*, 2020; Dwivedi *et al.*, 2019):

1- Public policy design and evaluation
2- Decision making process
3- Communication and interaction with different stakeholders including citizens
4- Introduction of and enhancement of services and products (new and existing)
5- Processes and approaches, through either improving existing processes or designing new ones.

Zooming in the case of public sector in specific, governments at different levels can play a dual role, i.e. adopt and implement AI technologies and/or regulate and govern the adoption and implementation of AI in other sector, just like put by Kuziemski & Misuraca (2020) to govern algorithms while governing by algorithms.

Misuraca & Viscusi (2013) classified government governance functions into three main categories; policy making, public services, and internal management. Noordt & Missiraca (2022) utilized this categorization and elaborated on the usage of AI related technologies in each one of those governance functions. Firstly, for policy making, AI related technologies in public sector can be used to quickly detect social issues, for example in traffic detection in Estonia, to improve the process of public policy decisions, then to monitor and evaluate the implementation of public policy, and finally to enhance the role and involvement of citizens in the policy making process, for example the launch of CitizenLab as an online community engagement platform for local governments in over ten different countries across the globe.

Secondly, for public services, AI can improve information provision, in addition to public service delivery in both G2B and G2C. Finally, internal management where AI can improve in innovation areas through developing new government services, in human resource areas such as allocation of people, recruitment services, in institutional cyber security, in maintenance of facilities, in financial management and anti-fraud and anti-corruption areas.

AI technologies on its own or integrated with other emerging technologies, e.g. Big Data (BD) or Internet of Things (IoT), can be applied in diverse domains in the Public Sector such as public policy development, and other sectors such as public healthcare, education, telecommunication, security and cyber security, public transportation and roads safety, power and energy in addition to utilities management, and finance and others (Kankanhalli *et al.* 2019; Androutsopoulou *et al.*, 2019; Sun & Medaglia, 2019), where this can be implemented through standalone projects or under smart government initiatives.

Governments worldwide have begun to adopt AI through developing advanced ICT systems, procuring such systems and implementing them for example using systems for automated decision making (ADM), or even predictive algorithms for the purpose of automating, assisting in or replacing humans from existing decision-making or taking processes (Schiff *et al.*, 2021). Taking an example of AI applications in public sector is adoption in smart traffic; where AI was used by Chinese government in transportation construction and management to improve the quality of traffic management and its efficiency, in addition to enhance transportation services such as the online ticketing systems (Ma *et al.*, 2018). Another key area where AI was applied was the healthcare sector, (Sun & Medagila, 2019) in which AI can help in areas of patients' documents management and mining records to diagnosis diseases and designing treatment plans.

There is increasing number typologies and researchers in the adoption and implementation of AI in government, nevertheless, Straub *et al.* (2022) discussed the need for a balanced account of AI for government (AI-GOV), due to the fact that those researches neither build nor acknowledge each other (Zuiderwijk *et al.*, 2021; Sousa *et al.*, 2019; Wirtz *et al.*, 2019). Furthermore, Madan & Ashok (2022) argued that there is a contextual gap and lack of processual understanding of Artificial Intelligence adoption and usage in public sector in the current literature and research on AI. Therefore, there is a critical lack in research that provides a better understanding of the consequences of embedding machine intelligence into government through offering a shared conceptual language and capturing the vast breadth of disciplinary perspectives.

Moreover, depending on the way they are used, integrating datasets, with large volume of quality data, with new advanced technologies within public services enable Artificial Intelligence systems to execute accurate tasks and could offer great benefits and value to users, (Noordt & Misuraca, 2022), whereas Mehr (2017) argued that the adoption and use of AI related technologies in public sector would lead to enhancing operations' efficiency and effectiveness and potentially increase government performance, nevertheless, little is known about the actual impact of AI related technologies on government processes (Bailey & Barley, 2019).

One aspect that can be taken into consideration when adopting AI in the public sector is the organizational enablers and their role in facilitating the adoption process. Firstly, a definition of Organizational Enablers (OE) is needed. Project Management Institute defines OEs as "*structural, cultural, technological, and human-resource practices*" that can be leveraged to support strategic plans and to implement initiatives and projects to achieve the organization's strategic objectives. Literature review showed that there is a scarcity of researches conducted to explore which organizational enablers are needed to be managed and implemented in order to successfully adopt AI in organizations. Nevertheless, Alhashmi *et al.* (2019) conducted a qualitative research to explore the critical success factors affecting the implementation of AI in the healthcare projects in the government of Dubai, through using the extended TAM model, and a modified proposed model was developed which included the following factors:

- Managerial:
    - Managerial factors included the influencers within the organization, organizational norms in the work environment, level of trust among employees.
- Organizational:
    - The organizational factors understudy were the fit in training, availability of UAE expertise, in addition to the presence of global partnerships.
- Operational:
    - The researchers studied the perceived enjoyment as a factor for accepting AI projects in healthcare sector
- Strategic:
    - The study considered users' satisfaction (doctors and projects leaders) as a key strategy success
- Information Technology (IT) infrastructure

The impact of above mentioned factors was explored/tested on both the perceived usefulness (PU) and on the perceived ease of use (PEoU), and the findings showed that all managerial, organizational, operational and IT infrastructure factors had positive impact on both PU and PEoU, whereas the strategic users' satisfaction showed a negative impact.

2.2.5 Smart government

Governments adopted ICT through different waves of initiatives that started with electronic government (e-government), then mobile government (m-government), or open government and currently shifting towards smart government initiative, which is an umbrella that AI, IoT, and Big Data analytics projects fall under (Kankanhalli *et al.*, 2019: Schedler *et al.*, 2019). Nevertheless, smart government is still not widely adopted in many governments across the globe, but setting the start of a new wave in governments' digitalization.

The smart government eco-system includes a diverse set stakeholders, such as different government entities, private sector, academia, societies and citizens just to mention a few. The collaboration between those stakeholders in smart government initiatives creates value for each of the relevant stakeholders (Neumann *et al.*, 2019), and enhances efficiency and creates value for citizens (Mikhaylov *et al.*, 2018).

The creation of public value in smart government is through joining forces and collaborative innovation approaches with different concerned stakeholders (Neumann *et al.*, 2019), and Mikhaylov *et al.* (2018) even argued that the cross-sector collaboration between public sector, private sector, and academia is required to capitalize on their strengths. This creation of shared value requires deep knowledge in different technologies including artificial intelligence, IOT and others, in addition to the availability of needed both technical and technological skills and competencies.

In order for the collaboration between the different sectors: public sector, private sector, and academia and merging their strengths to succeed, Mikhaylov *et al.* (2018) identified seven main collaboration success factors:

1. Facilitative leadership, where leaders in different parties build trust and commitment, encourage open communication and create a sense of ownership.
2. Shared objectives, where parties in a collaboration need to be aligned objectives which would guide the decision making process towards achieving the shared or aligned objectives
3. Knowledge gathering and sharing: where joint actions for gathering knowledge and sharing it are set between the collaboration members and standards for data collection and sharing are established in order to build the institutional and technical capabilities.

4. Communication, where the presence of a communication strategy has an effect on the management of the collaboration by showing the value of joint actions, by sharing positive learning feedback, and by building collaborative platforms.
5. Socializing: where leaders encourage transparency throughout all levels of the collaboration, and building an interconnected learning system to transfer knowledge across the collaboration.
6. Expertise, where hiring of expert people will induce trust and positively affect the quality of the service.
7. Sense-making, where the concerned leaders should make sense of the existing situation, and play roles accordingly, e.g. networking in cases of fragmentation, and this is usually affected by the phase which the collaboration process is in.

Adoption of "smartness" has been part of the government reform strategies worldwide, especially the ones turning into smart government. The study of Eom *et al.* (2016) focused on smart work in Korea from the users' perspective through adopting the Technology Acceptance Model (TAM). Smart work is considered as any means that organizes work and enables employees to work remotely through any convenient telecommunications means such as computer-based technologies and mobile devices. This will enable employees to conduct work activities and deliver regardless of time, or even physical place, which can be from home or remote working places.

The intention to adopt smart work is relatively high among both of the younger workers with lower salaries and shorter job tenures, as well as employees in quasi-governmental organizations, who actually utilize smart tools to do work more frequently than a variety of other work groups. Furthermore, they found that perceptions of commuting to and from work in addition to business trip costs, work productivity and efficiency, as well as organizational and technological support all contribute to the adoption of smart work by public employees. On the other side, intentions to adopt smart work are negatively affected by a different set of factors such as being socially isolated, a lack of communication, and unfavorable type of leadership and unfriendly management styles, which are associated with smart work.

There is interrelation between AI and other technology related initiatives, such as e-government, as AI plays a role in enhancing e-government systems, through a platform that integrates AI technologies with e-government systems in order to increase the level of trust, transparency and efficiency of the systems, in addition to increasing citizens' participation (Al-Mushayt, 2019).

AI adoption in the public sector has an impact from regulatory approaches perspective, e.g. the legal and policy tools and instruments in use, as Kuziemski & Misuraca (2020) discussed three case studies in three different democratic countries; Canada, Finland and Poland, which were selected based on meeting the following criteria:

1- Mid to high AI Readiness Index (Oxford Insights, 2019)
2- Diverse Socio-economic models of development

After analyzing different aspects such as the goals, the risks, and barriers, the research team concluded that using AI applications in public sector could play a role in exercising control over citizens depending on the nature of application being used, for example, the use of an ADM in the Canadian immigration process control system affected the judgement of who is allowed to enter Canada and who cannot, whereas the Polish case study citizens were classified based on their "goodness" to invest in for jobs; nevertheless, there is a need for a common framework for the purpose of evaluating the potential impact of adopting AI on public sector.

Gil-Garcia *et al.* (2014) discussed adoption of emergent technologies, nanotechnologies, and public sector innovation as being smart or turning the government into "smart government". In contradiction to other literature reviewed, the researchers presented the direction that there is no consensus on what the term "Smart Government" entails, or what its relation with both emergent technologies and innovation is. However, in order to get a better understanding of smart government, organizations should consider it as a mix of both emergent technologies and innovation that is to utilize both and not to focus on one part and ignoring the other.

Adopting and implementing AI in the Public Sector organizations was not a straightforward project or tasks, organizations faced different types of challenges that concerned people to take action(s) to resolve the issues.

2.2.6 Artificial Intelligence and other technologies

Schedler *et al.* (2019) found that smart Information and Communication Technologies (ICTs) adopted in smart government play a promising role in public sector services and are considered as the next step for electronic government and mobile government. Those smart ICT under the smart government initiatives would positively affect the relationship between government entities and their stakeholders, through enhancing the quality levels of services and communication. The research team proposed actions to overcome the barriers and diminish concerns identified that would hinder the successful implementation of smart government initiatives, for example organizations can establish new laws, regulations and policies, new business models, provide technical infrastructure, and open communication channels with stakeholders especially citizens.

2.2.6.1 Artificial Intelligence and Internet of Things (IoT)

Tang & Ho (2019) and Zekić-Sušac *et al.* (2020) viewed that adoption of Artificial Intelligence in the public sector can support other implemented smart initiatives such as smart cities projects. Those initiatives utilize enabling technologies, such as Internet of Things (IoT), and cloud computing, integrated with artificial intelligence algorithms, consequently, organizations need to develop those enabling technologies together and integrate them with the relevant functions, in order to, fully harvest the benefits of those technologies. For example, Zekić-Sušac *et al.* (2020) proposed the architecture of a machine learning based intelligent system for decision making to exploit the advancements in big data environments. The system aimed to predict and model energy consumption in smart city projects in public sector, which will lead to better energy management, and thus improving energy efficiency and sustainability efforts in the public sector.

Similarly, Kankanhalli *et al.* (2019) discussed how IoT and AI technologies could be integrated under smart government initiatives to enhance government efficiency, in addition to offering more value added services for citizens (G2C), businesses (G2B), and other public administration stakeholders, in a variety of areas, such as transportation, education, healthcare, public health and safety, in addition to utilities and energy management.

In the past period scholars like Lytras & Erban (2020), Ma *et al.* (2018) and Chatterjee *et al.* (2018) studied the element of integrating AI with an IoT engine in order to facilitate and enhance quality of e-government services and their efficiency in smart cities due to the use of digital and telecommunication technologies. For example, Chatterjee *et al.* (2018) studied, using the Information System Success Model, how the use of Internet of Things (IoT) is playing a crucial rule in the lives of modern city dwellers in India. It is necessary to integrate advanced technologies such as AI, Big Data, and IoT in 'Smart Machines' "*to simulate intelligent behavior to arrive at an accurate and reliable decision without human intervention.*" as their combination is becoming an essential prerequisite for the success of information system use in the organization, which is reached through positive users' intentions to use IoT and their satisfaction using IoT, and the increase use of IoT by citizens will generate more data which will be collected, analyzed and decisions taken using AI.

Ma *et al.* (2018) studied the role of AI in smart public services in China through the implementation of Internet of Things, which when powered by AI is referred to as "*Internet of Intelligent Things*". The Chinese government integrated the AI technologies such as Machine Learning Algorithms, and Deep Learning and others with IoT to offer smart public services, which included smart government services, smart traffic services, intelligent information management systems, and smart healthcare services. Moreover, the government identified new challenges that were not discussed in other literature, for example:

- Insufficient key intelligent technologies
- Patency of technology
- Lack of comprehensive regulations for the adoption and usage of AI technologies in public services

2.2.6.2 Artificial Intelligence and Big Data

In the past years, the magnitude of increase in the volume of data produced and shared between digital stakeholders, its value, velocity it is generated in, the variety and veracity, variability, and visualisation, is paving the way to an era of Big Data (BD) (Homlund *et al.*, 2020).

According to Löfgren *et al.* (2020), Big Data and practices utilized in machine learning, predictive algorithms and automated decision-making artificial intelligence, are shaping the future of service technology solutions through changing how decision-makers in and providers of public service foresee those technologies. Löfgren *et al.* (2020) identified issues related to data quality, data storage, access and security, data analysis, and finally data usage. For example, one of the main challenges that need to be taken into consideration when adopting Big Data enabled AI systems is digital inequalities, due to the reason that in-equal opportunities of citizens' and service users' to use of and to access digital technologies, will lead to creating a bias in smart city data collection processes and equal segmentation of data, and thus decisions made.

It is worth to mention that data governance and big open and linked data (BOLD) impact big data algorithmic systems (BDAS) Janssen *et al.* (2020), therefore, organizations; public and private, need to develop data governance approaches in order to overcome the challenges facing data management, and benefit from potential opportunities of such technologies.

(Pencheva *et al.*, 2020) studied the role of AI and big data in the public sector, its applications and challenges for adoption, then its potential implications on governments, for example enhancing efficiency and accuracy, increasing accountability and trust of citizens, optimizing cost and productivity, in addition to establish real-time monitoring and evaluation systems.

2.2.7 Artificial Intelligence Challenges and Issues

Literature reviewed identified and listed different AI challenges, and based on the types of those challenges, they were classified into general challenges and public sector related specific challenges (Dwivedi *et al.*, 2019), in addition, a third classification was added based on its relation to other technologies such as BD and IoT.

2.2.7.1 General AI Challenges

The general AI challenges are similar to the challenges faced when adopting new technologies, which are around resistance to change, data integration and substitution of employees with machines (Dwivedi *et al.*, 2019).

Organizations in general, including public sector ones, need to evaluate the feasibility of adopting and implementing CCS to yield desired outcome(s). This evaluation would be across three proposed phases of designing, developing, and deploying CCS, and through assessing the four elements of data, technology, the organization and the surrounding environment in each phase, Furthermore, Desouza *et al.* (2020) identified main challenges in each phase.

Design Phase

Data Element: The challenge of availability of data, ease of accessibility and collection, and its analyzability and cleansing are issues organizations can face when adopting CCS.

Technology Element: The challenge the organizations could face would be from two aspects: infrastructure and capability, i.e. the availability of needed qualified skills, resources, and IT applications, either in-house or externally through partnership or outsourcing.

Organization Element: The challenge would be in the organizations ability to understand their own capabilities; both its strengths and weaknesses, and then act accordingly to build on their strengths and tackle the weaknesses to ensure needed competency is available.

Environment Element: The challenge would be sharing information between organizations to enable a quality scan of the external environment, in other words the willingness of other parties to share and exchange data would be a challenge for the concerned organization.

Development and Deployment Phases

Data Element: The challenge in organizations is the unintentional bias of data and algorithms, which will affect the application quality of decisions or outcomes.

Technology Element: The challenge in organizations would be the availability of suitable tools to monitor and audit bias in systems.

Organization Element: This challenge is more related to the availability of in-house qualified and competent human resources in the organizations.

Environment Element: In the development phase, this element is tracked to the technical issues with the same challenge of availability of suitable tools to control and audit the systems.

2.2.7.2 Public Sector AI-related-Challenges

As previously mentioned, research on AI technologies in the public sector is still in its nascent stage, as there is very little empirical research to support AI acclaimed benefits or challenges, some studies covered the challenges in public sector from the perspective of key stakeholders (Sun & Medaglia, 2019) and others identified the AI challenges in public sector in general (Dwevidi *et al.* 2019). Both studies agree on the following AI general challenge dimensions: social; economic, ethical; political, legal and policy related, organizational and managerial related, data, and technological (Sun & Medaglia, 2019; Dwevidi *et al.*, 2019).

Based on the analysis of research results for the adoption and usage of AI in healthcare, Sun & Medaglia (2019) framed different challenges within each dimension as perceived by each stakeholder group. To govern the adoption of AI in public sector, Sun & Medaglia (2019) forwarded four recommendations for government leaders to follow:

1- Evade adopting a single view on AI, on the contrary managers should assemble a multi perspective policy guidelines for AI that serve the needs and expectations of different stakeholders
2- Adopt adaptive governance strategies that cater for stakeholders different views
3- Prepare AI related guidelines prior to developing the AI applications
4- Ensure setting up required tools for the governance of AI

As previously mentioned, adopting CCS initiatives goes through three phases of designing, developing and deploying (Desouza *et al.*, 2020). Public sector organizations can follow strategies that would tackle the challenges and overcome the above-mentioned issues to enhance the organizational adoption approaches of CCS projects.

Schedler *et al.* (2019) based on thirty two semi-structured interviews conducted with smart government's stakeholders in Switzerland have identified seventeen barrier variables that are classified under six groups of barriers that Public sector organizations adopting "smart government" initiatives face, as shown in Table (2-2) Smart Government Barriers Groups in Switzerland. Depending on the nature of those groups, they are distributed under two main barriers; organizational and institutional barriers. Cost-benefit related, innovation related, and technical infrastructure issues are considered organizational barriers, as this is faced inside a public administration and its departments. While the other three are regarded as institutional barriers because they occur outside the boundaries of organization and set the framework, within which organizations work.

Table 2-2: Smart Government Barriers Groups in Switzerland

Groups	Barriers	Barrier Variables
Organizational Barriers (Internal)	1- lack of technical infrastructure	1- Technical infrastructure
	2- cost-benefit considerations	2- Political resources 3- Contested benefits 4- Efficiency 5- Scarce financial resources
	3- lack of innovation capacity	6- Readiness for Innovation 7- Risk-aversion 8- Management support 9- Skills and Know-how
Institutional Barriers (External)	4- lack of legitimacy	10- Discomfort 11- Citizens' response
	5- lack of legal foundations	12- Legal foundation
	6- lack of policy coherence	13- Silo Thinking 14- Political System 15- Plurality 16- IT Standards 17- Long-term thinking

Androutsopoulou *et al.*, (2019) tackled the issue of improving the communication between citizens and public sector organizations through an innovative web platform that is based on a specific AI technology, namely chatbots, which have comprehension abilities to spoken speech using AI NLP, Machine Learning, and data mining technologies.

Existing digital communication channels between citizens and government face a dilemma as it is characterized by lower cost, yet on the other side, there is no deep richness and expressiveness. In order to overcome this shortfall, Androutsopoulou *et al.* (2019) aimed to develop a rich and expressive digital communication channel that suits the needs of citizens especially, in cases of complex, and ambiguous interactions, which also introduces some new challenges pertaining to the nature of public sector service delivery; mainly the codification of knowledge into a format to enable the machines to exploit them, second challenge is related to the quality of data, in addition there are some ethical issues that hinders the adoption of AI related technologies such as lack of trust in machines' intelligence, in addition to the fear of workers' replacement by machines.

Suksi (2020) tackled the legal issues the Finish public administration faced in adopting and using automated decision-making (ADM). The researcher pointed out that there is an increase in the use of automated decision-making, and a shift from industrialized-based-rule of law towards digitalization-based-rule of algorithm, which will affect the administrative due process when automated in general, and when specifically artificial intelligence algorithms are introduced.

Some studies discussed the issue of trusted data. (Liu *et al.*, 2019) tackled the AI normative implications resulting from using AI tools and algorithms in government functions. A case in the USA, "State vs. Loomis", was examined to identify different types of risks and challenges associated with "alogrithmization" of functions, due to 'legal black box', and 'technical black box' issues which results from the lack of transparency in decision making process in AI techniques .

Both studies (Suksi, 2020; Liu *et al.*, 2019) call for actions by governments. (Liu *et al.*, 2019) call to ensure equal opportunities and transparency of the due processes and to eliminate bias and discrimination in courts, and government in general. Whereas, Suksi (2020) is calling for national governments to identify, review and update their laws and legislations to ensure the presence of adequate preventive legal safeguards and to implement them to consistently maintain the rule of law, and control the degree of AI applications use, especially ADM, in Public Administration. Furthermore, the development and adoption of a data governance framework for big data algorithmic systems can assist in mitigating and controlling issues related to governance and ethical concerns such as lack of transparency and low accountability, trust, fairness and discrimination (Janssen *et al.*, 2020).

(Marget & Dorobantu, 2019) argue that in order for governments to achieve their core tasks, they need to understand data and algorithms; nevertheless, they have been slow in adopting AI. The research team took the example of London Metropolitan Police and presented the five types of challenges the police had faced in their adoption of AI facial recognition algorithm. First challenge was the low accuracy technology due to lack of in-house expertise, weak ability to attract talented people due to unattractive packages in comparison to private sector, and difficulty to evaluate outsourced work and quality of deliverables or work done. Second challenge was the failure risk, which would affect the trust in government entities in case of not delivering. Third, the need for more transparency to assure public trust and confidence.

In addition, the researchers proposed future guiding steps for governments to follow, for instance, they recommend cooperating with independent academic researchers to get assistance in optimizing adoption of technologies, and in addition, governments should give more attention to ethical side of AI and develop the needed frameworks.

There are challenges that face AI from public policy perspective, (Valle-Cruz *et al.*, 2020) conducted systematic analysis on forty nine scientific articles published between 2010 – 2019 in journals concerned with public administration and policy. The purpose was to get a better understanding of decision making processes in the public sector, its complexity, in addition to parties concerned with these processes. The paper aimed to assess the integration of AI in the public policy-cycle by building on the *Dynamic Public Policy-Cycle (DPPC)* conceptual framework. Utilizing AI, this framework has the potential role in public policy monitoring throughout DPPC, and to turn the process into a more dynamic one through instantaneous adjustments, which will lead to a more informed decision-making process. Whereas, Dwivedi *et al.* (2019) argues that there is a challenge due to absence of a unified framework for "*Public Policy Challenges of AI*" which would help in analyzing AI for public use as countries are identifying different sets of challenges varying from trust, transparency, and privacy to changes in regulations and global networking and collaborations as main or critical challenges.

Fountaine *et al.* (2019) discussed that focusing on cutting-edge technologies and talent is not sufficient for AI projects to succeed or scale up in organizations. The issue from researchers' perspective was that there was not enough focus on and break down of organizational and cultural barriers. To overcome those barriers, organization's leaders must work on creating a shared vision, communicating with employees, anticipating obstacles and managing resistance to change, shifting minds, focus the budgets on integration and adoption practices in addition to technology, then they should identify the suitable organizational model with clear roles and responsibilities for concerned functions and teams, work on educating everyone, and finally reinforcing change through role modeling, accountability with clear ownership of projects, and incentivizing employees.

The above mentioned challenges were around the organization itself, Mikhaylov *et al.* (2018) looked at challenges from another perspective, and identified a set of challenges that affected the cross sector collaboration success such as:

1- The difference in surrounding environment for private and public sectors.
2- The difference risk management approaches.
3- Static logic operational model in public sector vs. hybrid market and corporate logic in the private sector.
4- The difference in organizational structures and statutory requirements between private and public sectors.
5- Different organizational cultures and employees mindsets, and uniting the cultures around one vision instead of "us and them".
6- AI related skills gap difference between sectors.
7- The need to build trust and thus data sharing relationships.

2.2.7.3 Other technologies (Big Data and IoT) related Challenges

Adoption of Big Data in public sector faces issues that range from technical to moral ones which Pencheva *et al.* (2020) classified them under three tiers; system level, organizational level, and individual level. Under system level, the challenges are the ones at the government level, not pertaining to a single organization, and they are identified as challenges regarding privacy and security of data, then data governance and finally ethical barriers or challenges.

As for the second tier, which is concerned with Big Data challenges on organizational-level, the identified challenges are around lack of collaboration and siloed operational approach, organizational culture and change management, the availability of needed resources and skills, and involvement of concerned expertise in the organization in the redesign process, the need to improve and update the technological infrastructure. The third tier is concerned with the barriers or issues at the individuals' level where those challenges are related to risk appetite at decision-making level and the lack of consistent leadership to steer the process, in addition to resistance to cooperate by individual data owners, and the lack of understanding of Big Data potentials and the lack of adoption of Big Data mindset.

IoT-enabled AI applications could enhance the public services, and the regulations and governance frameworks around those services, which would lead to a better citizens' life, nevertheless, those applications and services encounter several challenges in the their development and implementation, which are classified into two main categories discussed below (Kankanhalli *et al.*, 2019):

Category 1: Application-related-challenges.

Category 2: Ethics-related-challenges.

The challenges of category 1: Application related challenges are classified into three main points:

Interoperability of systems: Internally, organizations will face the issue of interoperability of the systems that comprise the IoT and AI technological infrastructures that they adopted, in addition to be interoperable with other systems in external organizations with whom they collect or share data.

Data privacy and security: Since IoT depends on the internet for connection, which means that data is subject to cybersecurity threats and theft, and since data is stored across different locations, this imposes issues in data maintained in hybrid systems. In addition to the issue of privacy invasion and hacking, and the ambiguity of nature of data collected and who is benefitting from users/citizens data.

Sustainability: This challenge is concerned with energy consumption from environmental sustainability perspective. Even though IOT – AI enabled applications can assist in managing energy consumption, but at the same time they could consume large amounts of energy to function

2.2.8 AI and Ethical issues

Governance of AI is key to ensure ethical AI is adopted and implemented. Dwivedi *et al.* (2019) identified that the lack of governance in AI affects its potential benefits and increases the risks. Adoption of AI and its underlying technologies entails ethic-related challenges or issues, which can adversely affect the adoption and usage of AI in organizations (Kankanhalli, *et al.*, 2019; Marget & Dorobantu, 2019; Sun & Medaglia, 2019). Those challenges can be classified into:

1- *Accountability issues:* There are certain scenarios with accountability issues when command is given but has adverse outcomes such as the cases in healthcare of wrong medications given by doctor or patient ordering merciful-killing.

2- *Transparency issues:* The decision making process in AI technologies is a black box one, and due to this fact, the decision making process is not observable by auditors to ensure fair decisions. Dwivedi *et al.* (2019) identified this lack of transparency as algorithm opacity challenge.
3- *Bias (lack of fairness) issues*: Applications could be racial or unfair in the decision made because of biased training (Sun & Medaglia, 2019), biased algorithm programming used in the AI system (Sun & Medaglia, 2019; Dwivedi *et al.*, 2019), or hidden complexities which would result in reinforcing discrimination or undesired outcomes (Dwivedi *et al.*, 2019).
4- *Trust issues*: Citizens and especially in healthcare sector lack the trust in AI –based decisions (Sun & Medaglia, 2019; Androutsopoulou *et al.*, (2019).
5- *Data sharing issues*: The abuse of citizens' data through misuse and the sharing of private data of citizens pose a challenge for commercial purposes to private sector (Sun & Medaglia, 2019).
6- *Creation of filter bubbles public spheres*: AI systems might cause societal fragmentation and radicalization depending on the filters they use, which will affect the governments' capabilities to be perceived as legitimate and get public opinion support.

2.2.9 Artificial Intelligence in the Public Sector in the United Arab Emirates

Artificial Intelligence has quickly become one of the key strategic components in various countries' strategic plans across the globe, however the AI adoption and usage process by government(s) is still slow (Zhang *et al.,* 2021). Nevertheless in 2017, the United Arab Emirates Federal Government named a Ministry of State for AI, to reflect its future vision of the importance of Artificial Intelligence and confirm its commitment towards the adoption of global technological revolution (Al Badi *et al.*, 2022). This ministry's primary goal is to support the UAE government in its AI adoption journey, through providing them with the appropriate innovative environment, and enhance AI adoption in the different public sector organizations, and within the different governmental sectors, for example health, education, and infrastructure.

Halaweh (2018) adopted the term "Intelligent government - Gov. 3.0" or "AI Government" to label the digital government in the United Arab Emirates (UAE), and considered it as the third generation of digital government, as it succeeded the e-government and smart/m-government. The UAE cabinet launched its AI Strategy to enhance government performance, overcome challenges through the utilization of smart digital systems and become the leader in AI investment in various sectors.

It is worth mentioning that despite that Alhashmi *et al.* (2019) studied the critical success factors for implementing AI in projects in healthcare system; nevertheless, the factors understudy did not cover it from the organizational enablers' perspective.

2.2.10 Data Management:

Data management is defined as "*a group of activities relating to the planning, development, implementation, and administration of systems for the acquisition, storage, security, retrieval, dissemination, archiving and disposal of data*" (Office of the Deputy Prime Minister, 2005). Whereas, Liu *et al.* (2022) looked at data management from the decision making perspective and defined it as the practice of collecting, protecting, processing, storing and organizing data for targeted business decisions. Organizations in the corporate world consume the data in a scattered manner which would ultimately enhance the importance of the data management process for sound decision making based on vast data sets, therefore, by deploying the appropriate people, implementing pertinent policy processes, and utilizing appropriate technologies, data management ensures availability of accurate quality data and enhanced accessibility to large data stores. In essence, it is a collection of old and new best practices for managing and governing large volumes of data.

Mikalef & Gupta (2021) argued that managers in organizations considered data as one of the critical elements in leveraging the potential of AI systems, and is regarded as a corporate asset and the quality of data for training of AI systems and learning, and the operation of AI applications is of high importance (Ransbotham *et al.*, 2018). In addition data management construct is crucial to the adoption and usage of AI in organizations as the data labeling, confidentiality, security and control is affected (Janssen *et al.*, 2020; Desouza *et al.*, 2020; Mikhaylov *et al.*, 2018; Löfgren *et al.*, 2020; Pencheva *et al.*, 2020; Sun & Medaglia, 2019; Dwevidi *et al.*, 2019; Liu *et al.*, 2019).

Al Nuaimi *et al.* (2015) argued that in order to ensure the usability and integrity of data for decision-making, it is imperative that data is regularly cleansed, integrated across departments, and normalized according to the requirements of its users. As organizations move to Big Data, data security becomes more complex, influencing the decision to adopt innovative tools. The availability, reliability, and accessibility of useful data can be greatly enhanced by effective Big Data management. Moreover, Zaki (2019) discussed several aspects of the organization's digital transformation aspects, highlighting the significant role of data in rewriting business models for organizations to be more data-driven. Consequently, organizations should consider in their management of data the type of beneficial data gathered, its acquisition internally or externally through different means, and finally the refinement of and effective utilization of data.

2.2.11 Organizational Culture:

Barney, (1986) defined Organizational culture (OC) as a "*set of beliefs, values, and assumptions that are shared by members of an organization*", whereas, Zheng *et al.*, (2010), considered OC as the environment in which organisational activities occur. Paais & Pattiruhu (2020) referred to organizational culture as the set of customs, values and attitudes within the organizational settings that influence the performance and productivity of the entire organization via influence over specific essential cores. Consequently, people rely on the organizational values to guide their decisions and actions, and the behavior of its members (Schein, 1985); in other words, OC guides the behaviors of employees to know their work environment (Wagner & Hollenbeck, 2005), in addition to know how to deal with problems (Schein, 2010).

The focus on OC has increased since the 1980s, Organizational Culture (OC) has become a business phenomenon that is used to assist organisations to adapt to the surrounding environment (Denison 1990; Zheng *et al.*, 2010). In particular, a research team headed by Denison identified and validated four dimensions of OC; adaptability, consistency, involvement and mission, as shown in (Figure 2-2) Denison Culture Model.

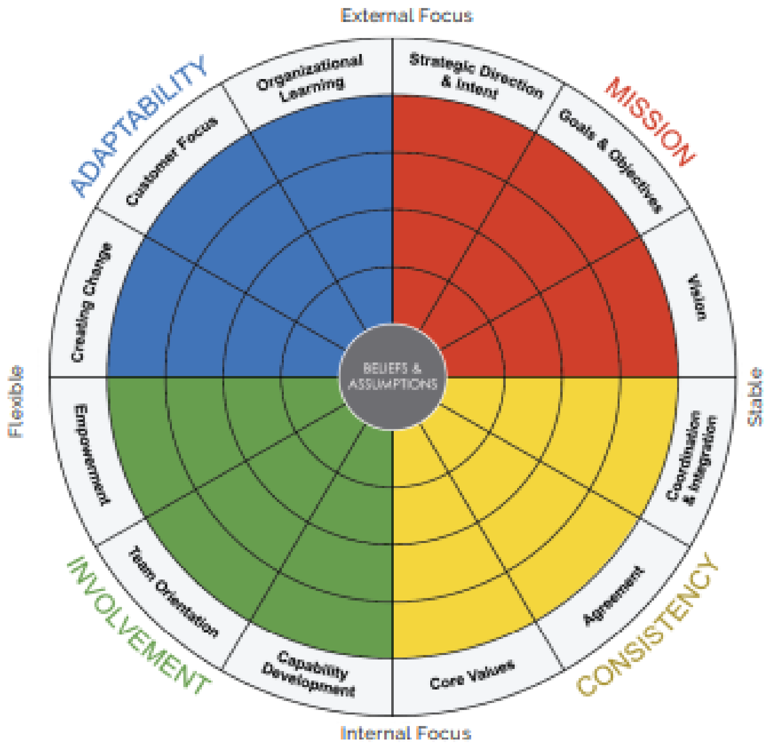

Figure 2-2: Denison Culture Model (Source: Fey and Denison, 2003)

This Denison Organizational Culture Model measures four critical traits of culture of an effective organization, in which each of those traits is further broken down into three indices (Denison, 1990; Denison and Mishra, 1995; Fey and Denison, 2003). Figure (2-2) shows the 2 levels of traits and its relevant indices.

Adaptability refers to "*the degree to which an organisation has the ability to alter behaviour, structures, and systems in order to survive in the wake of environmental changes*". The indices of the adaptability trait are creating change; customer focus; and organisational learning.

Consistency refers to "*the extent to which beliefs, values, and expectations are held consistently by members*", and its indices are: coordination and integration; core values; and agreement.

Involvement refers to "*the level of participation by an organisation's members in decision-making*"; its indices are: empowerment; teamwork; and capability development.

Mission refers to "*the existence of a shared definition of the organisation's purpose*", with indices strategic direction and intent; goals and objectives; and vision.

In this research, the Denison Culture Model is the model that is used to measure Organizational Culture.

2.2.12 Digital Organizational Culture (DOC):

In the recent years new digital technologies, which encompass combinations of computing, information communication and connectivity, have emerged and affected societies, organizations and individuals. Within organizations, Martinez-Caro *et al.* (2020) proposed the development of a digital organizational culture (DOC) to facilitate the business digitization process, which is considered by Hess *et al.*, (2016) as the organization's way to identify, explore, and utilize the new digital technologies, or simply how to adopt technology.

DOC is concerned with the what the new digital advancements and can bring to the organization– with a focus on the core data related functions: storing of data then processing it, and finally transporting it (Carr, 2003), which results in business digitization or processes automation. Whereas, Vodanovich *et al.,* (2010) used the term "digital culture" to refer to a work environment that is molded and impacted by digital tools and technologies. In organizations that have established advanced digital cultures, a majority of workers utilize digital technology to work together faster and easier, building connections while working remotely, automate repetitive processes, create new ideas, and provide customers/citizens with access to products, services, and assistance. In this study the Deshpande & Webster's (1989) definition was adapted for digital culture and conceptualized as the "*Set of shared assumptions and understanding about organizational functioning in a digital context*".

As previously discussed, organizations comprise of groups of individuals, and it is those corporate values, the groups' mindsets and activities characterize organizational culture (OC) and define how thing are done in the organization, since organizations constitute of unique groups of leaders managers, and employees to realize a unified vision, therefore organizations tend to have their own distinctive culture (Munoz & Degnan, 2021).

Martinez-Caro *et al.,* (2020) noted that whenever digital technologies are introduced and adopted then the ways how work is done and how the organization interacts internally and externally will face serious changes. Moreover, redefining work culture is a prerequisite for the successful reinvention of work methods, which truly applies in the case of digitalization.

To adopt new technologies or integrate them, organizations in addition to enthusiastic and competent, they also need a strong organizational digital culture (Vial, 2019).

The organizational digital culture refers to the cultural values, norms, and behaviours related to the adoption and use of digital technologies within organizations which impacts operating models and value creation in organizations (Busco *et al.,* 2023; Vodanovich *et al.,* 2010), Moreover, (Duerr *et al.,* 2018) argued that in the era of digital transformation or digitalization, the organizational culture must expand to include its digital workplace practices. Workplace practices include the organizational policies and programs that organizations implement to improve employees' well-being in addition to organizational effectiveness (Grawitch *et al.,* 2006), and in the digital era this includes the practices affected by the digitalization and how people approach work (Colbert *et al.,* 2006). These changes can be manifested in the form of changes on organizational structures, new internal collaboration approaches, and novel external collaboration ways, in addition values and norms are concentrated around digitalization, and finally the need to encourage innovation and integrate employees' creativity with new digital strategy (Martinez-Caro *et al.,* 2020; Duerr *et al.,* 2018).

Having that said, Organizational Culture in the digital era can evolve, by generating needed changes to adapt to new practices by capitalizing on its strengths which support a new digital approach, and which can reinforce the practices in both formal and informal ways. Following this, the organization can build its digital culture (Martinez-Caro *et al.,* 2020). Digitalization, fueled by the innovation of new technologies and new ways of operating and business models, is changing both society and organizations (Pradana *et al.,* 2022). In response to the rapidly expanding and disruptive digital technologies, organizations are implementing organization-wide digitalization initiatives to address both new risks and opportunities (Imran *et al.,* 2021). This "digitalization" is a colloquial term for incorporating digital technologies into organizational operations and customer/citizen interactions (Baker, 2014; Vial, 2019). Artificial intelligence and cybersecurity are technologies that fall under digitalization.

On the other hand, Artificial intelligence (AI) is considered as a subset of digital transformation and digitalization processes (Soori *et al.,* 2023). Organizations adopting and implementing Artificial Intelligence (AI), respond to technological changes in different ways, depending on how AI is impacting their organizational culture and how their OC absorbs AI technologies and their changes in the organization. This resulted in what is known as Organizational AI Culture (OAIC); the organizational culture in organizations adopting AI (Munoz & Degnan, 2021), which includes the cultural values, beliefs, and practices within that organization that support adoption of AI technologies throughout the different phases of development to implementation. This OAIC is characterized by the organization's ability to continuously learn, respond, and adapt quickly to the innovations, to disruptive technologies, and to changes made through the digitalization journey for the benefit of both internal and external stakeholders, in addition to the organization's ethical attitude towards AI implications, while at the same time staying true to their main goals and corporate values. Therefore, OAIC affects the quality of existing employees and the ones to hire, the knowledge and training needed for new technologies and processes, in addition to updating organizational policies to suit the new changes. In organizations adopting AI the need to align strategy with the new technology, their customer/citizen expectations, in addition to changes in surrounding environment.

In general, there is an overlap between organizational digital culture (DOC) and organizational AI culture (OAIC); an organization with a strong digital culture may be more likely to embrace AI technologies, nevertheless, there are specific cultural values, for example ethical values and transparency, and practices that are necessary to develop and implement AI technologies.

2.2.13 Intention to Continue Usage of AI system(s)

Several researchers studied the continuance usage of technology, based on the concept that continuance is considered as the persistent use of the adopted or used technology beyond its first use (Bhattacherjee, 2001) or the continuous implementation of technology on a regular basis, where one of the measures used for technology continuance is the intention to continue usage (Hernandez-Ortega *et al.,* 2014). Intentions to continue using technology are closely tied to actual use and pertain to anticipated future consumption or usage.

Abdul Rahman *et al.* (2019) studied the critical success factors for continuing to use an IS system; digital library in a military-context, and introduced continuation of usage intentions to an extended successful model with net benefits and user satisfaction as variables from DL IS Success Model (2003) and concluded that net benefits was one of the variables that influenced the intention decisions to continue using technology.

The intention to continue usage is measured by intention to continue usage (Hong *et al.*, 2006: Abdul Rahman *et al.*, 2019), future frequency and regularity of usage, and intention to use adopted technology than alternative technology or means (Abdul Rahman *et al.* (2019).

2.2.14 Artificial Intelligence (AI) and Information Systems (IS)

2.2.14.1 Information Systems (IS) – Technology Adoption Theories:

Artificial Intelligence (AI) as a technology falls under the umbrella of Information Systems (IS). IS refer to a group of interrelated components that facilitate information collection (or retrieval), processing, storage, and distribution in an organization (Laudon & Laudon, 2014). It generally refers to a computer-based system used to provide specified information to an organization in a specific context in order to facilitate its operations (Livari, 2005).

There are several theories and models for the adoption of Information and Communication Technologies (ICT). In this section, the IS theories, referred to in the reviewed literature in previous sections, are presented and assessed for suitability based on proposed criteria, then the relevant model(s) to examine the success of adoption and implementation of AI in Public Sector organizations will be proposed. Table (2-3) shows a summary of the main IS theories mentioned in the reviewed literature.

Table (2-3) IS Models/Theories mentioned in the literature review.

IS Theory/Model	**AI related literature review**
Technology Acceptance Model (TAM)	(Narain *et al.*, 2019; Chatterjee *et al.*, 2018; Eom *et al.*, 2016)
Unified theory of acceptance and use of technology (UTAUT)	(Chatterjee *et al.*, 2018; Eom *et al.*, 2016)
Technology-Organization-Environment Framework (T.O.E.)	(Tang & Ho, 2019)
Diffusion of Innovation Model (DOI)	(Tang & Ho, 2019)
Fountain's framework for Technology Enactment (TEF)	(Schedler *et al.*, 2019; Eom & Kim, 2014; Eom *et al.*, 2016)
Delone & McLean IS Success Model	(Chatterjee *et al.*, 2018; Eom & Kim, 2014)

2.2.14.2 Technology Acceptance Model (TAM):

Davis (1989) introduced the Technology Acceptance Model (TAM) as an adaptation of Theory of Reasoned Action (TRA), and it focused on the individual user's behavioral intentions and attitude to accept and use technology. It is one of the most reviewed and widely used IS acceptance theories (Narain *et al.*, 2019; Tamilmani *et al.*, 2020) especially in the areas of identifying acceptance determinants. The decision to accept and use technology is affected by two internal factors; perceived usefulness (PU), and perceived ease of use (PEOU) as shown in Figure (2-3), in addition to external variables such as social influence. In general, the model is used to examine the main factors that influence the technology acceptance decision on user's level.

TAM, as an Explain and Predict Theory (Gregor, 2006), is concerned with explaining the acceptance of technology based on user's perceptions, how easy the users perceive the understanding and use of an IS or technology, in addition to their perception to the degree that positive impact or amount of benefits would be provided through adopting the technology, which consequently will lead to their decision to accept or reject the introduced technology, and thus predicting their behavioral intention to use. This acceptance/rejection decision is a phase that precedes adoption of technology and measuring the success of this adoption.

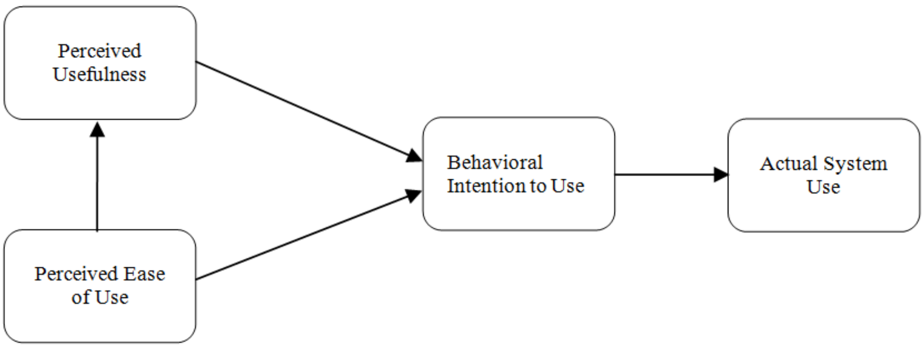

Figure (2-3): Technology Acceptance Model (TAM) from Davis (1989)

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

Venkatesh *et al.* (2003) reviewed the IT acceptance models and formulated the Unified Theory of Acceptance and Use of Technology (UTAUT) is an extension to TAM after studying eight technology adoption models (Tamilmani *et al.*, 2020).

The model focuses on organizational users – on individual level (Oliveira & Martins, 2010); as it explains the individual acceptance and usage decisions in an organization. The UTAUT Model proposes three core independent determining factors for "Behavioral Intentions", which are performance expectancy, effort expectancy, and social influence. The behavioral intention as a variable in addition to facilitating conditions are two key variables influencing the "Use Behaviour". The model also comprises of four key moderators; gender, age, voluntariness, and experience, as shown in Figure (2-4).

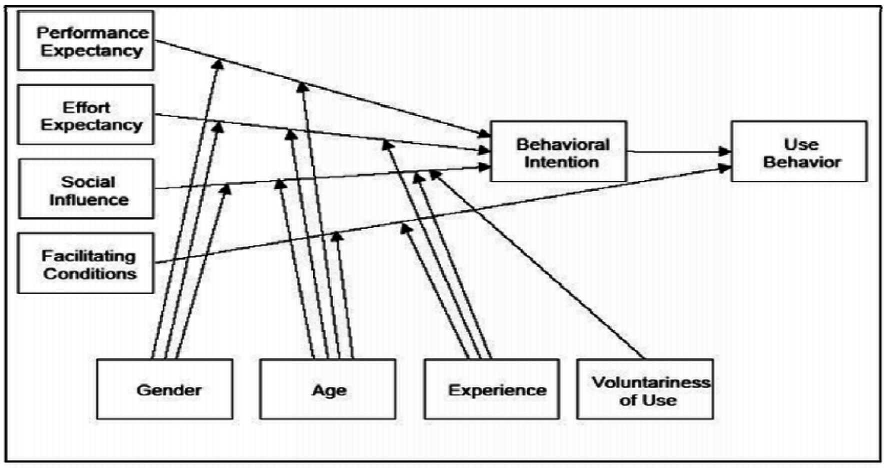

Figure 2-4: UTAUT Model from Venkatesh *et al.* (2003)

One of the interesting variables in the UTAUT model is **Performance Expectancy (PE)** which has been defined as "*the degree to which an individual believes that the system helps to improve job performance*". Nevertheless, and according to Gallivan (2001), it is worth to mention that when organizations rather than individuals adopt technologies and innovations the use of theories such as TAM and others are not entirely suitable due to their lack of consideration of key organizational and environmental factors, in addition TAM and UTAUT theories are at the users level as per Oliveira & Martins (2010).

2.2.14.4 Technology – Organization – Environment (TOE) Framework

Technology-Organization-Environment Framework (TOE) was developed in 1990 by Tornatzky and Fleischer as a technology or innovation adoption framework at the organization-level (Gangwar *et al.*, 2015), and regardless of its size and industry it is in (Wen & Chen, 2010) in different contexts (Baker, 2011). TOE would enable the organization understand the different significant factors impacting the adoption of new technology from organizational context, and consequently identifying and describing those organizational components that affect the organization’s adoption decision because they can bring new opportunities or challenges to the adoption of technologies (Saldanha & Krishnan, 2012).

TOE Framework proposed that the adoption is dependent on the variables in three main areas; technology, organization, and environment as depicted in Figure (2-5). The technological variables are concerned with the internal and external relevant technologies in use or available to the entity, in addition to the characteristics of those technologies. The organization variables cover organization specific factors such as size, scope, communication processes, and managerial structures. Lastly, the environmental variables are related to external factors such as the industry the entity is operating in, the market structure, the competitors’ landscape, and the relationship with government (Oliveira and Martins, 2010). Therefore studying and analyzing those factors can be used for the purposes of adoption of IS and technology innovations on organizational level.

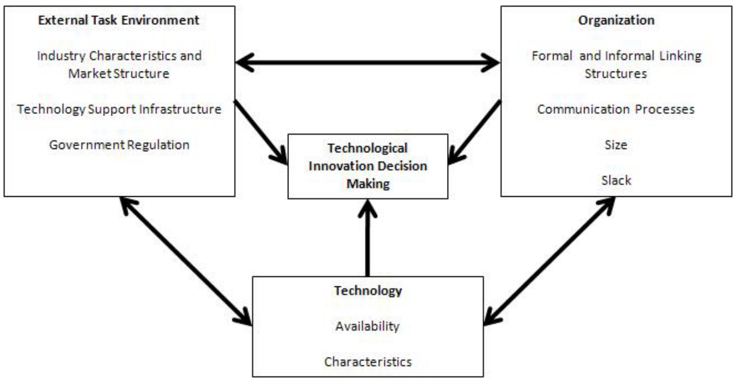

Figure 2-5: Technology-Organization –Environment Framework (Tornatzky and Fleischer, 1990)

According to TOE Framework, there are three different perspectives to be taken into consideration when predicting variables affecting adoption of any technological innovation, and those are technology, organization, and environment (Oliveira & Martins, 2011). From TOE framework standpoint, technological factors include both technologies used inside the premises of organization and off premise technologies, and include both equipment (hardware) and process. The factors includes those technologies that are already in use, or available in the market but not currently used by the organization (Oliveira *et al.*, 2014).

The technological dimension describes the features of the currently used technologies in addition to the new technologies related to the organization as it can cause changes (Baker, 2012; Tornatzky & Fleischer, 1990). This dimension includes several aspects such as the technology relative advantage or value added, compatibility and integration, and complexity vs simplicity of the technology and digital and cyber security concerns in the organization when adopting technologies (Ahmadi *et al.,* 2017). Previous studies also related the technological dimension to the assessment of the new technology benefits over its adoption cost (Lin, 2014). The technology aspect encompasses both internal and external technologies that are pertinent to the organization. The organizational aspect is related to the descriptive measures of the organization, including size, scope, management structure, and internal resources. Lastly, the environmental aspect is related to an organization's industry, competitors, and government policy on intent (Chong & Olesen, 2017). It helps researchers and practitioners understand how these three factors influence each other and shape organizational outcomes.

Organizational dimension contains the features, properties, and attributes and refers to descriptive measures such as organization size, managerial and organizational structure, in addition to the availability of resources that are needed to enable the adoption process (Baker, 2011; Alsaad *et al.*, 2017; Tornatzky & Fleischer, 1990). This also includes the internal factors of the organization, such as its structure, culture, resources, and capabilities. The organization's readiness for change, its ability to absorb and adapt to new technology, and its overall innovation orientation play a crucial role in the adoption and successful implementation of technology.

While, the environmental context explains the features of the surroundings and the industry in which an organization operates (Baker, 2011; Tornatzky & Fleischer, 1990), which includes operating domain and structure of an organization, and the regulatory sector, in which organizations operate and competitive pressure (Tornatzky & Fleischer, 1990; Oliveira & Martins, 2011; Alshamaila *et al.*, 2013). This also includes interactions with stakeholders, such as; government, competitors, and customers (Tornatzky & Fleischer, 1990; Wisdomet *et al.*, 2013).

Oliveira & Martins, (2011) argued that T.O.E. framework is more powerful in examining intra-organization technology adoption and usage, because as a framework it takes into consideration the environmental perspective. T.O.E. can be considered as a comprehensive framework which can be adopted on its own or alone or integrated in a hybrid model with other technology adoption theories to study successful technology adoption in different contexts (Al Hawder *et al.,* 2021).

2.2.14.5 Diffusion of Innovation (DOI) Theory

Diffusion of Innovation Model (Rogers, 1995) is concerned with organizational innovativeness, which is affected by both individual and organizational factors. Taking the organizational level first, the model proposed three independent variables; *leader characteristics* which affects attitude towards change and adoption of new innovation or technology, *internal characteristic of organizational structure* such as size of organization, degree of centralization in decision making, complexity of operations and expertize needed. The last variable is the *external characteristics of organizational* which is concerned with system openness that is the external environment which the entity operates in.

The Individual level from DOI model perspective is concerned with individuals apt to adopt innovation and technology, i.e. average time taken to adopt technology, (Rogers 1995) which is affected by different individual characteristics such as willingness, risk taking, skepticism, accordingly individuals were categorized into five categories; *Innovators, early adopters, early majority, late majority, and laggards* (Oliveira & Martins, 2010). Moreover, the adoption decision on individual level and the rate of adoption are affected by how the potential adopter perceives the change positively or adversely, or innovation in terms of potential benefits, compatibility with ones' values and experiences, complexity of new technology, degree of trialability, and finally the observability which is related to observing the results of the technology of innovation. Table (2-4) shows the effect of each perceived dimension

Table 2-4 Effect of DOI perceived dimensions (Oliveira & Martins, 2010)

Perceive dimension	**Effect on rate of adoption**
Relative advantage	Positive (+)
Compatibility	Positive (+)
Complexity	Negative (-)
Trialability	Positive (+)
Observability	Positive (+)

2.2.14.5 Technology Enactment Framework (TEF)

Jane Fountain published in 2001 her study "Building the Virtual State", which was about the penetration and adoption of Information Technology in the public sector organization in the United States of America. This study conceptualized the Technology Enactment Framework (TEF), which consisted of explanatory elements clarifying the adoption of technologies in public sector organizations: Objective of IT – elements of IT in use, Organizational forms – internal factors, institutional arrangements – external factors, enacted technology, and outcomes – impacts of adopted IT on organizations on both structures and behaviours. The framework as shown in Figure (2-6) is used in identifying elements that affect the enactment of IT in public sector organizations and how individuals and units in organizations perceive IT and how it will affect their interests, therefore can be used on organizational level.

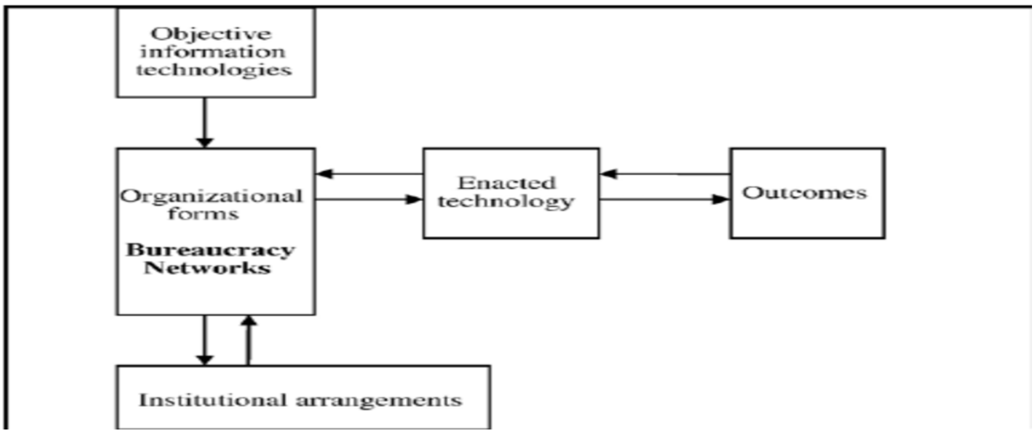

Figure (2-6): Technology Enactment Framework (Fountain, 2001, p. 11).

2.2.14.7 Delone & McLean IS Success Model

In 1992, Delone & McLean published a study on dependent variable in IS research which resulted in a model called "DM IS Success Model". This model comprised of multi-interrelated-dimensions that consisted of "*systems quality*", "*information quality*", and "*use*", "*user satisfaction*", "*individual impacts*" and "*organizational impacts*". In year 2003, Delone and Mclean reviewed and updated their model where "*Service quality*" was introduced to the model, "*Intension to use*" was added before "*use*", and "*Individual Impact*" and "*Organizational Impact*" are replaced with "*Net Benefits*".

System Quality: is defined as "*the desirable characteristics of an information system*" (Petter *et al.*, 2008), it is concerned with the technical success level regarding the outputs produced by the system as information is needed to perform tasks or conduct periodic activities (Wang & Lin, 2012). This would cover system characteristics such as system flexibility and customizability (Ahn et. al., 2004; Al Mamary *et al.*, 2014), ease of use, ease of learning, system reliability, intuitiveness, sophistication of the system, response time (Al Mamary *et al.*, 2014).

Information quality focuses on the desirable characteristics of the system outputs (Delone & Mclean, 2003; Petter *et al.*, 2008). For example relevance, understandability, completeness, consistency, accessibility, timeliness (Lee *et al.*, 2002; Al Mamary *et al.*, 2014), accuracy (Newcomer & Claude, 1991; Al Mamary *et al.*, 2014), usability (Al Mamary *et al.*, 2014).

Service quality is measured in terms of the level of quality of support services offered by the information system's provider or developer. This construct was assessed in different studies through measures such as service assurance, and degree of responsiveness by the concerned systems support functions, as well as providing quality training to users.

Intention to use/Use: Delone and McLean (2003) proposed the intention to use and use variables to their model. Basically, the notion of "*Intention to use*" is adopted from Fishbein and Ajzen (1975) Theory of Reasoned Action (TRA), which aligned predictions of doing a behavior with the intentions to do it.

When it comes to technology adoption or IS success model, the intention to use/use variable is concerned with evaluating the context in which technology is used (Ojo, 2017). Petter *et al.* (2008) considered *"system use*" as the degree and manner of use and utilization of an IS by users who can be staff and/or customers. It can be measured through different measures, e.g. "amount of use", "frequency of use", "nature of use", "appropriateness of use", "extent of use", and "purpose of use" (Al Mamary *et al.*, 2014). The difference between "Intention to use" and "Use" is "in case of intention then it measures the user's attitude, while in case of "use" then it is perceived as a behaviour. As previously mentioned, DeLone and McLean (2003) and Wang & Liau, (2008) argued that depending on whether the context, the variables "use" and "intention to use" can be applied alternately, that is in the cases which involve mandatory or voluntary usage.

User satisfaction: This variable is often measured by overall user satisfaction and is considered as one of the most important measures of systems success, (DeLone and McLean, 2003).

Net benefits: The updated version 2003 IS success model of Delone & McLean combined organizational impact and individual impact under the net benefits variable, which is also considered one of the measures of IS success, and it extends to measure how the IS benefits stakeholders. DeLone and McLean (2003) proposed that it has been measured by sometimes assessing individual impact or organizational impact.

The Delone & McLean IS success model and its updates have been studied and validated and widely employed in a number of studies related to implementing technology and information systems effectively in a variety of fields and subjects. According to a number of studies, the variables of DM IS Success Model have demonstrated effective capabilities for assessing the success of adopting IS in different areas such as in hospitals and healthcare facilities (Bossen *et al.*, 2013; Cho *et al.*, 2015), in learning and education management systems in Higher education institutes (Lin, 2017; Ajoye & Nwagwu, 2014), and virtual education systems including e-learning or online learning (Holsapple & Lee-Post, 2006; Chuo *et al.*, 2015; Mahmoodi *et al.*, 2017).

2.2.14.8 Evaluation and selection criteria:

Selecting the most appropriate IS model is critical in IS research. Despite the presence of many technology adoption theories, in this research the six models to be evaluated are the ones referred to in the literature review in previous sections in this chapter. This section will present critical reflection and the evaluation and selection of IS acceptance model(s) that will be used in this study.

According to Oliveira & Martins (2011), there are several theories that are used the most in field of technology adoption or acceptance, which are TAM, UTAUT, DOI Theory and T.O.E. While DOI Theory and T.O.E. Framework are utilized at an organizational level, TAM and UTAUT are generally implemented at an individual level.

The Technology Acceptance Model (TAM) developed Davis (1989) is among the most influential research models to determinate the adoption of IS at the level of the individual user. TAM is the most commonly reviewed technology acceptance model by previous researchers; Surendran (2012) describes TAM as one of the most commonly used research models to predict the use and adoption of information systems and technologies by individual users. Agrawal (2013) refers to TAM, as one of the most widely used research models to determine the determinant of the adoption of IS/IT, in the study of the determinants of the uptake of IS/IT. Nevertheless, TAM has been questioned for failing to provide practitioners with actionable guidelines (Lee *et al.,* 2003), and has received numerous criticisms for its use as a framework for identifying technology acceptance at individual's level, regardless of the quality and efficiency of the technology involved (Meerza, 2017). The model over-simplifies the technology acceptance (Shachak *et al.*, 2019), research has highlighted TAM's inability to address the link between technology and real usage of technology (Ajibade, 2018). In his review of the TAM model, Ajbade (2018) cited many researchers and scholars such as Zahid *et al.* (2013) and Bashange (2015) who had criticized the model; according to Zahid *et al.* (2013), the TAM does not take into account external elements such as age of the user(s) and their education level which might impact acceptance and desire to adopt technology.

Furthermore, a number of findings in studies revealed TAM's limitations in explaining user behavior (Hai & Alam Kazmi, 2015; Lim *et. al.,* 2016). It was also suggested that the TAM model could not adequately forecast the adoption of ICT, hence there is a need for another model to predict technological acceptance (Hojjati & Khodakarami, 2016). Additionally, Ajibade, 2018) argued and criticized the TAM model that it cannot explain individual behavior (. Furthermore, this model is insufficient to explain users' adoption and usage of new technology, particularly in the context of digitalization, for example adoption of e-government related technologies (Chandio *et al*., 2017).

Since Venkatesh et al. (2003) proposed the Unified Theory of Acceptance and Use of Technology (UTAUT), many researchers adopted this model to try to explain IS acceptance, while others criticized and argued that the model's moderators are not suitable for all contexts or it lacked needed variables to explain IS acceptance and usage such as attitude towards technology. Other researchers noted that there is a need to reconsider the relationships between the model's constructs, as few studies used the full moderators, for example the model assumes that the users can use technology voluntarily, whereas in some cases, it is mandated by the management of the organization, and thus all employees have to adopt and use the technology.

Another criticism to UTAUT is concerning the effect of proposed predictors on technology usage, as it has been designed to be mediated through usage intention. Therefore when considering this perspective, other technological, organizational and social components are limited down to individual users' perceptions, Moreover, UTAUT similar to TAM focus on the aspect of "acceptance" in the technology implementation process (Shachak *et al.*, 2019), and this does not take into consideration the implementation continuation. A common criticism to both TAM and UTAUT is that currently their contribution to current knowledge is becoming flat, as most of the studies using the models are consistent with the findings obtained in relation to usage intentions.

The third theory is the Diffusion of Innovation (DOI) theory has been critically studied by several researchers for example Lyytinen & Damsgaard (2001); Zanello *et al.* (2016); and Lundblad *et al.* (2003). Many of those researchers share the interest in studying the impact of DOI on organizational improvement. Despite being considered as a groundbreaking contribution to the field of innovation studies, the DOI suffers from several drawbacks which limit its scope, there is evidence that innovations often are not diffused within and across organizations to achieve improvement, that is due to DOI's linear and source-dominated nature which views the communication process only through elite's eyes, it makes it a weakness. The theory focuses on communication as an element for innovation, nevertheless, the role of media is undervalued in the theory as it singles out certain people who are instrumental in distributing ideas, and the theory assumes that people influenced by media are limited to innovators, early adopters or opinion leaders whose impressions affect others' viewpoints. Yet, the media is capable of facilitating group conversations that are guided by agents of change.

The DOI hypothesis also fails to understand that while some adopters exhibit qualities of innovators/early adopters, they may be slow to accept an innovation / invention owing to personal views or other considerations.

Finally, the DOI theory should fully identify the interaction between the different elements of innovation, adopter, social system, and other parameters influencing adoption, with a focus on how these parts of the theory relate to the diffusion of innovation within organizations.

Technology Enactment Theory (TEF) is a theoretical model that aims to provide a systematic and explanatory approach to understanding the process of implementing and integrating new technologies within government organizations and the effects of implementing those technology. TEF examines impact of organizational arrangements such as laws and regulations, and organizational forms, for example, centralizations, or communication channels on technology implementation in public sector, this framework offers valuable insights into the complex dynamics involved in the successful adoption and use of technology. However, there were several studies for example Gong *et al.,* (2020); Norris, (2003); Schellong, (2007); and Yildiz, (2007) covered both the strengths and limitations of TEF.

One of the key strengths of the TEF is its emphasis on the social and organizational aspects of technology enactment. It recognizes that technology implementation is not simply a technical endeavor but involves multiple stakeholders, social dynamics, and contextual factors. The framework provides a comprehensive model that incorporates four interrelated dimensions: Task, Actors, Context, and Technology. By considering these dimensions, the framework highlights the need to align technology with specific tasks and understand the diverse perspectives and roles of actors involved.

Moreover, the TEF framework acknowledges the importance of iterative and dynamic processes in technology enactment. It suggests that technology implementation is not a linear process but rather a cyclical one, where continuous feedback and adaptation are necessary for success.

However, the TEF also has some limitations that should be considered. Firstly, the framework lacks a clear methodology or set of guidelines for operationalizing its concepts. While it provides a theoretical foundation for understanding technology enactment, it does not offer practical steps or tools for organizations to follow. This can make it challenging for practitioners to apply the framework effectively in real-world contexts.

Secondly, the framework's focus on the social and organizational aspects of technology enactment may overshadow technical considerations. While it is crucial to recognize the social and organizational impact of technology, neglecting technical factors can hinder the successful implementation and integration of complex technological systems.

Additionally, the TEF could benefit from further exploration of power dynamics and political factors within organizations. Technology implementation often involves negotiation, conflicts of interest, and power struggles. Integrating these aspects into the framework would provide a more nuanced understanding of the challenges faced during technology enactment.

The fifth model is the Technology – Organization – Technology Framework: According to Oliveira & Martins (2011), T.O.E. Framework, as originally introduced and later refined in the context of IT adoption research, provides an analytical framework which can be applied to the study of the uptake and absorption of various types of IT innovations.

Researchers and practitioners use the T.O.E. Framework to guide their analysis of technology adoption and implementation processes. According to Baker (2011) extensive research has demonstrated the wide-reaching and illustrative utility of the T.O.E. Framework in a wide range of technical, industrial and national/cultural contexts. Nguyen *et al.* (2022) further asserted the widespread of T.O.E. and through a survey of literature demonstrated that T.O.E. is repeatedly used to exhibit the organization's intention to adopt a variety of innovation domains, including Artificial Intelligence (AI), customer relationship management (CRM) (Cruz-Jesus *et al.,* 2019), ICT (Eze *et al.,* 2019), e-business (Putra & Santoso, 2020), Big Data (Park & Kim, 2021), e-commerce (Linh, 2022), digital advertising (Cho et. al., 2022), social commerce (Abed, 2020), and social media marketing (Abbasi, 2022). By considering the technological, organizational, and environmental factors, they can better understand the dynamics at play and develop strategies to facilitate successful technology integration within organizations.

The TOE model emphasizes the interplay between these three factors. It suggests that the successful adoption and implementation of technology require a fit between the technology, organization, and environment. A misalignment in any of these areas can create barriers and challenges for technology adoption, while alignment can lead to positive outcomes such as improved performance, innovation, and competitive advantage.

Although there is a large body of research that uses T.O.E. Framework to investigate the elements that influence the adoption of technical breakthroughs, the conclusions are dispersed (Sophonthummapharn, 2008). Ramdani *et al.* (2009) suggested that T.O.E. is limited by a lack of well-integrated or well-developed variables, and that further research into organizational adoption is necessary. Low *et al.* (2011) have also noted that the framework has not significantly evolved, and that the factors in each unique circumstance must be taken into account, additionally, Xu & Li (2013) argued that the main constructs and variables are not concise and differ depending on the context, Oliveira *et al.* (2011) have recognized that other variables must be further refined in order to achieve the desired outcome, such as sociological variables and cognitive variables, as well as the ability to leverage IT investments through different channels, professionals' competencies, the managerial capacity of change management, and variables relevant to the country context, such as public policy / regulation, ICT infrastructure, and culture. Musawa & Wahab (2012) stated that there is a lack of power of technology and that the adoption variance is not explained

Furthermore, researchers in different empirical studies have applied slightly different factors to the T.O.E. frameworks for technological, organizational and environmental contexts (Baker, 2011). In general, researchers have agreed with the findings of Tornatzky & Fleischer (1990) that the T.O.E. Framework influence adoption. Nonetheless, they have then assumed that there is a distinct set of factors for each particular technology or context under study. For example, in the study of Zhu *et al.* (2004), one relevant factor for the technological dimension that influences e-business adoption is technology readiness. Similarly, in the organizational dimension, other factors such as firm size, global scope, and financial resources are perceived relevant to the adoption of e-business. Finally, when researchers want to know how the environmental framework impacts e-business adoption, they need to look at factors such as regulatory environment and competition intensity. Different types of innovations or different national/cultural contexts will have different factors that affect their adoption. (Baker, 2011).

While the Technology-Organization-Environment (TOE) Framework provides a useful model for understanding the dynamics of technology adoption and implementation, it has certain limitations that should be acknowledged. To begin with, the T.O.E. Framework is very adaptable as it gives the researchers the ability adjust the variables or metrics depending on each new study environment. Consequently, researchers have found no need to modify or refine the theory itself.

The T.O.E. Framework has been labeled a "generic" model (Zhu & Kraemer, 2005). This finding is acceptable given that the theory has evolved to be employed as a framework within which a variety of components may be put. Baker (2011) gave numerous reasons for the limitations and lack of development in the T.O.E. Framework; the framework witnessed very little change because it has been considered as congruent with other theories of innovation adoption rather than giving a competing explanation; there are various theories and models about technology or innovation adoption. The T.O.E. framework is not the only option accessible to researchers for explaining organizational adoption of technology or innovation. DOI idea is arguably the most comparable explanation to T.O.E. (Rogers, 1995). Another limitation covers the simplification of the complex interactions between technology, organization, and environment into three broad categories. This oversimplification may not fully capture the nuanced and multifaceted nature of these factors, potentially overlooking important variables and relationships.

The T.O.E. Framework tends to focus on the static aspects of technology adoption and implementation, without explicitly considering the dynamic nature of these processes over time. It may not adequately address the evolving nature of technology, organizational changes, and environmental shifts that can influence the outcomes. In addition, the T.O.E. Framework model acknowledges organizational factors, such as culture and resources, nevertheless, it may not sufficiently emphasize the role of individuals and human behavior in technology adoption. Factors like user acceptance, motivation, training, and resistance to change can significantly impact the success or failure of technology initiatives.

The T.O.E. Framework often treats technology, organization, and environment as separate dimensions or factors, not fully exploring the interactions and feedback loops between them. In reality, these factors are highly interdependent, and changes in one area can trigger ripple effects in others. Ignoring these dynamic relationships may limit the framework’s explanatory power. The T.O.E. Framework is a general framework that does not account for the unique contextual factors that can influence technology adoption and implementation in different industries, sectors, or organizational settings. It may not adequately capture the specific challenges and opportunities faced by organizations operating in diverse contexts.

While the T.O.E. Framework helps in understanding the factors that influence technology adoption, it has limited predictive capability. It does not provide a precise roadmap for predicting the success or failure of specific technology initiatives in specific organizational contexts.

Despite these limitations, the TOE Framework remains a valuable theoretical framework for studying the interactions between technology, organization, and environment. However, researchers and practitioners should be mindful of its boundaries and consider incorporating other relevant theories and frameworks to provide a more comprehensive analysis.

Reflecting on the sixth model; The Delone and McLean IS Success Model. This is one of the most popular models used to measure the success of IT implementation and use. It has had a significant impact on information systems research. However, the model is not without criticism. The main criticism of the D&M IS Success Model is that it focuses only on measuring the success of the system and neglects other important factors such as the organizational impact. There is a lack of contextual factors as the does not take into account contextual factors that affect the success of the information systems. For example, the model does not consider the impact of organizational culture, the leadership support, the training of users, and other situational factors, therefore, the applicability of the model may vary from one organization to other.

Some critics argue that the model focuses too much on user satisfaction as a measure of system success. User satisfaction is important, but it does not cover the whole spectrum of user experiences and outcomes. The model does not explicitly consider factors like user engagement or user resistance, nor does it consider subjective perceptions of users outside of satisfaction. Another areas of criticism, is that while the model provides a conceptual framework, critics argue that it does not provide a strong theoretical foundation to understand the causal mechanisms behind system success. They argue that the model fails to explain how the factors it identifies interact and interact in a causal way.

Finally, the model focuses on short-term system success, and does not take into account the sustainability of information systems or the changing nature of systems. It does not consider system maintenance and system evolution, nor the need for continuous system improvement and updates.

Some critics claim that the model's constructs are complex and difficult to measure. They also claim that the model does not provide clear guidance on how to operationalize and measure the factors that are identified. This can lead to different interpretations and inconsistent assessments of system success when using the model.

Although there are some limitations to D&M IS Success model, it has made a great deal of progress in understanding the complex factors that affect information system success, but researchers and practitioners need to consider these limitations while complementing the model with different theories and approaches.

First criterion for selection is to have the referred to model or framework as a model or framework for technology adoption and implementation, and then the second criterion for selection is technology in organizations to ensure alignment with the research question, which is about organizational enablers/success factors. Third criterion is related to applicability of adoption in organizations.

Table 2-5: Models/Framework evaluation and selection criteria

	TAM	**UTAUT**	**DOI**	**TOE**	**TEF**	**D&M**
Technology Adoption Model/Framework	Yes	Yes	Yes	Yes	Yes	Yes
Alignment with research Question(s)	Partial	Partial	Yes	Yes	Yes	Yes
Organizational context	No	No	Yes	Yes	Yes	Yes

Two models were found to be suitable for this organizational context study and met the proposed models evaluation and selection criteria, the first model is the DM IS Success Model (2013) and selected constructs from this model is adopted. The other model is the T.O.E. Framework, and since it can be considered as a comprehensive framework which can be adopted on its own or integrated in a hybrid model with other technology adoption theories to study successful technology adoption in different contexts, T.O.E. Framework is integrated with the DM IS Success Model (2013) to form a hybrid model to answer the main research question, and achieve the research objectives.

2.3 PRIOR RESEARCH AND KNOWLEDGE GAP

This section presents prior research in the area of concern for this study, and highlights its potential contributions. The adoption of AI in public sector is considered as nascent, nevertheless, research and practice communities around the world are paying increasing attention to the use of AI applications in public sector. Examining and investigating "*What is the impact of organizational constructs on the intention to continue adoption of Artificial Intelligence in Public Sector Organizations in the United Arab Emirates*?" has not received focus in the literature and there are few empirical studies related to this issue, Madan & Ashok (2022) argued that the current literature and research on Artificial Intelligence lacks a contextual and processual understanding of AI adoption and in public sector. Medaglia *et al.*, (2023) pointed out that there is a shift in AI research field from mapping risks of AI and its benefits towards systematic analysis of how public sector would benefit from or face challenge due AI technologies design and adoption in government, with relatively little theorizing or unboxing of processes and mechanisms, and that there is a need for research community to pay more attention to areas of AI governance, data governance, and trust in AI and in the mechanisms that build trustworthiness.

Haenlein & Kaplan (2019) had a concern that AI will result in different unique challenges, such as legal, ethical and philosophical challenges that need to tackled, and future research is needed in those areas. Wirtz *et al.*, (2019) discussed a 4-AI-challenge model for public sector organizations; AI ethics, AI society, AI technology implementation, and AI Law & regulations challenges, and proposed future research opportunities to check those identified challenges from cross-national perspective.

Over the past decades, there has been a focus by Information Systems researchers on identifying determinants of technology use (Godoe & Johansen, 2012), and, there are several technology adoption models that have been used to understand the intention to adopt and use new technologies (McLean & Osei-Frimpong, 2019). Artificial intelligence (AI) has become a top technological priority of institutions (Mikalef & Gupta, 2021), in addition, Zhang *et al.*, (2021) are encouraging future research on AI adoption and use in governments across different national cultures, and the use of more quantitative analysis methods to analyse factors influencing adoption and usage.

AI technologies can reshape governments and how they function and deliver value to citizens and customers (Starub *et al.*, 2022), and there is a hype in adopting AI on governments levels, nevertheless, there is a need for more empirical research to analyse from multiple levels the AI-based systems for government; AI-GOV concept introduced by Straub *et al.*, (2022), for example from procedural perspective, or from how AI might affect governmental decisions making.

Maier (2021) discussed that the U.S. government implemented a national initiative that involved acceleration of AI/ML research and development, in addition to empowering the concerned workforce through training. Despite that, there is a need for studying public challenges that might affect the adoption of AI technologies challenge. Whereas Madan and Ashok (2021) concluded with a need for a future research agenda to address important research questions regarding understanding a process-oriented view of the AI phenomenon in public administration.

Fountine *et al.*, (2019) discussed that the technology was not the biggest challenge to building an AI-powered organization. The researchers proposed that the organizational culture is the biggest issue facing the entities, as most of leaders still run their organizations with mindsets and practices that are counter to those needed for AI technologies. Martinez-Caro *et al.*, (2020) study resulted in identifying the strong correlation between digital organizational culture and organizational performance through use of digital technologies, and thus shifting from traditional culture towards a digital culture might improve the performance, therefore there is a need to study in detail the impact of organizational culture including digital culture on the adoption and use of technologies.

With the emergence of fourth industrial revolution concept, the United Arab Emirates followed the new technological trends and shifted towards adoption of AI related technologies, and launched its first AI strategy in 2017 (Halaweh, 2018) with a vision to become the world leader in AI by 2031 (Shamout & Abu Ali, 2021). This strategy will build on the success of its previous strategy in smart government, and public sector entities are required to adopt AI across customer service to improve lives and government through delivering public value by making people in the UAE safer, healthier and happier. Some researchers covered the adoption of AI from leadership capabilities perspectives (Al Marzooqi, 2018), others covered certain targeted sectors such as adoption of AI in healthcare sector (Al Hashemi *et al.*, 2019; Al Badi *et al.*, 2021), and from agile policymaking perspective (Al Dhaheri, 2020). In summary, there was no study found that tackled the issue of AI technologies adoption and usage continuance in public sector organizations in the United Arab Emirates. (Table 2-6) summarises a sample of studies relating to this research.

Table 2-6: Summary of Main Related Studies

Title	Author(s)	Summary / Main finding(s)	Definition & Literature	Linkages with Variables						
				OC	DM	SQ	DOC	AU	OP	ITCU
The DeLone and McLean Model of Information Systems Success: A Ten-Year Update	Delone and Mclean, 2003	This is an updated model of the 1992 DM IS Success Model. Since role of IS changed over years, and so the model needed to be updated to cope with the changes. The model's usefulness needed to be evaluated in light of these changes.	√			√		√	√	
Information Systems Success: The Quest for the Independent Variables	Petter *et al.* 2013	A qualitative study that examined the literature on the independent variables that affect IS success; 43 specific variables - including system quality, use, and net benefits - posited to influence the different dimensions of IS success. These success factors were organized into five categories based on the Leavitt Diamond of Organizational Change: task characteristics, user characteristics, social characteristics, project characteristics, and organizational characteristics.	√			√		√	√	
Visualizing Benefits: valuating Healthcare Information System Using IS-Impact Model	Davidson *et al.*, 2020	A quantitative study that presented a modifed IS-impact model against an existing Public Health application. Some items for SQ were tested	√			√				
Automating and informating: roles to examine technology's impact on performance	Bravo *et al.*, 2016	This quantitative study showed that the technological factors affect the usefulness differently depending on the role it plays, which can be providing *informating* role and/or *automating* role. These two roles play a mediating impact on the relation between technological factors (information quality and system quality) and usefulness factors.	√			√				

Table 2-6: Summary of Main Related Studies - continued

Title	Author(s)	Summary / Main finding(s)	Definition & Literature	Linkages with Variables						
				OC	DM	SQ	DOC	AU	OP	ITCU
Understanding the impact of digital service failure on users: Integrating Tan's failure and DeLone and McLean's success model	Mustafa *et al.*, 2020	IS adoption was covered from a different perspective. Tan's failure model and DM ISSM were integrated to study the failure of digital services. The study identified 3 types of failures: Functional, system, and service with factors falling under each type of failures	√			√				
Effect of Student Satisfaction on Learning Quality and Learning outcome among Malaysian Undergraduate Nursing Students	Ching & Maarof, 2021	The conceptual framework developed for the study was based on DM ISSM (2003). This study found that system quality and service quality (e-learning quality) are correlated with student satisfaction (user satisfaction) and indirectly influenced e-learning outcome (net benefit) through a mediator variable (user satisfaction).	√			√				
Artificial intelligence capability: Conceptualization, measurement calibration, and empirical study on its impact on organizational creativity and firm performance	Mikalef and Gupta, 2021	Using RBV theory, the study developed and validated a framework on AI capabilities from organizational context, which would affect organizational performance. Data was identified as one of the AI capabilities that is affected by eight types of complementary resources that must be developed, and which jointly contribute to the emergence of an overall AI capability	√		√					
Big data analytics and firm performance: Findings from a mixed-method approach	Mikalef *et al.*, 2019	Data management plays a role in the adoption of technologies such as Big Data. Data analytics has a strategic importance, which impacts performance, and should not be perceived as a solely technical challenge	√		√				√	

Table 2-6: Summary of Main Related Studies - continued

Title	Author(s)	Summary / Main finding(s)	Definition & Literature	Linkages with Variables						
				OC	DM	SQ	DOC	AU	OP	ITCU
Corporate Culture and Organizational Effectiveness	Denison, 1990	Identification of organisational cultural model with four cultural traits; Involvement, Consistency, Adaptability and Mission. Each trait is measured with a set of items.	√	√						
Diagnosing organizational cultures: Validating a model and method	Denison *et al.* 2006	Introduced a model of organizational culture and its influence on organizational effectiveness. 60 items were validated	√	√						
Building the AI-Powered Organization	Fountaine *et al.*, 2019	The key to capture Ai fully and benefit from its applications is to understand the organizational and cultural barriers AI initiatives face Organizations need to lower challenges which means shifting their employees away from traditional mindsets	√	√						
Digital technologies and firm performance: The role of digital organizational culture	Martínez-Caro *et al.*, 2020	Research model was proposed and tested, proposing that the development of "DOC" would benefit the organization through facilitating both the business digitisation journey, and value-generation from digital tools, which would result in improving organisational performance.	√				√			
An extension of Delone and McLean IS success model with self-efficacy: Online learning usage in Yemen	Al Dholay *et al.*, 2018	The study proposed an extension to the DM IS Success Model with a focus on one determinant affecting user satisfaction and actual usage in the context of online learning platform.	√					√		
Artificial Intelligence in Government: Taking Stock and Moving Forward	Medaglia *et al.*, 2023	Application of AI from Policy perspective The study presented an overview of some of the main policy initiatives across the world in relation to AI in government	√							

Table 2-6: Summary of Main Related Studies - continued

Title	Author(s)	Summary / Main finding(s)	Definition & Literature	Linkages with Variables						
				OC	DM	SQ	DOC	AU	OP	ITCU
The impact of big data on firm performance in hotel industry	Yadegaridehkordi *et al.*, 2020	The study covered the adoption of BD and its impact on firm's performance. A theoretical model based on integration of Human-Organization-Technology fit and T.O.E. frameworks was proposed with a set of variables affecting big data adoption.	√						√	
Critical success factors of the continued usage of digital library successful implementation in military-context: An organisational support perspective	Abdul Rahman et. Al., 2019	Identifying the CSF successfully implementing Digital Library in a military context in Malaysia The study focused on intentions to continue using technology (i.e. Digital Library) and assisted in identifying ITCU items.	√							√
Understanding continued information technology usage behavior: A comparison of three models in the context of mobile internet	Hong *et al.*, 2006	A quantitative study that examined the utility of 3 prospective models for understanding and explaining the continued IT usage behavior. This study assisted in the identification of ITCU items.	√							√
A Brief History of Artificial Intelligence: On the Past, Present, and Future of Artificial Intelligence	Haenlein & Kaplan, 2019	This study introduced an AI definition, in addition to presenting the history and past of AI in addition to a comprehensive outlook on the future of AI	√							
Artificial intelligence in public services: When and why citizens accept its usage	Gesk & Leyer, 2022	A quantitative study that tested a model on the acceptance of AI in public service, and its impact on enhancing service efficiency and quality	√							
Designing, developing, and deploying artificial intelligence systems: Lessons from and for the public sector	Desouza *et al.*, 2020	Cognitive Computing Systems (CCS) application in public sector from 4 perspectives: data, technology, environmental, and organizational	√	√	√					

Table 2-6: Summary of Main Related Studies - continued

Title	Author(s)	Summary / Main finding(s)	Definition & Literature	Linkages with Variables						
				OC	DM	SQ	DOC	AU	OP	ITCU
Artificial Intelligence (AI): Multidisciplinary perspectives on emerging challenges, opportunities, and agenda for research, practice and policy	Dwivedi *et al.*, 2019,	A perspective on various aspects of AI from invited expert contributors from different sectors (public sector and others). The study assisted in the identification of AI applications both opportunities and challenges (in 7 main areas), and assessment of its impact.	√							
AI governance in the public sector: Three tales from the frontiers of automated decision-making in democratic settings	Kuziemski & Misuraca, 2020	This paper cover adoption of AI (automated decision making systems) in the public sector from governance and regulations perspective. The paper aimed to examine how the use of AI in the public sector in relation to existing data governance regimes and national regulatory practices can be intensifying existing power asymmetries. This paper called for a common framework to evaluate the potential impact of the use of AI in the public sector.	√							
Mapping the challenges of Artificial Intelligence in the public sector: Evidence from public healthcare	Sun & Medaglia, 2019	An empirical basis which helped in identifying a set of AI challenges in the public sector – healthcare disciplines The study covered the topic of governance of AI in the public sector and proposed four sets of guidelines for governance.	√							

Table 2-6: Summary of Main Related Studies - continued

Title	Author(s)	Summary / Main finding(s)	Definition & Literature	Linkages with Variables						
				OC	DM	SQ	DOC	AU	OP	ITCU
Administrative due process when using automated decision-making in public administration: some notes from a Finnish perspective	Suksi, 2020	The study covered the legal issues in the automated decision-making (ADM) process in public administration from a Finnish perspective. There is an increase in the use of automated decision-making, and a shift from industrialized-based-rule of law towards digitalization-based-rule of algorithm, which will affect the administrative due process when automated in general, and when specifically artificial intelligence algorithms are introduced.	√							
Artificial Intelligence and the Public Sector—Applications and Challenges	Wirtz *et al.*, 2019	Identified a set of opportunities and challenges for public sector use of AI applications	√		√	√				
Artificial intelligence for the public sector: results of landscaping the use of AI in government across the European Union	Noordt & Misuraca, 2022	Explored the use of AI in Public Sector, and the benefits in different areas such as policy making, and service delivery	√							
Beyond State v. Loomis: Artificial Intelligence, Government Algorithmization, and Accountability	Liu *et al.*, 2019	AI tools are being used to automate decision-making and are having a significant impact on individuals' rights and obligations State v. Loomis, a recent case in the United States, well demonstrates how unrestrained and unchecked outsourcing of public power to machines may undermine human rights and the rule of law	√		√					

Table 2-6: Summary of Main Related Studies - continued

Title	Author(s)	Summary / Main finding(s)	Definition & Literature	Linkages with Variables						
				OC	DM	SQ	DOC	AU	OP	ITCU
Artificial Intelligence powered Internet of Things and smart public service	Ma *et al.*, 2018	Integration of AI with IoT can enhance the power of both technologies AI technologies are expected to be widely applied to IoT applications to collect data, share data and analyze data. The AI powered IoT is referred as Internet of Intelligent Things.	√							
The race for an artificial general intelligence: implications for public policy	Naudé & Dimitri, 2020	Steering the development of an Artificial general (or super) intelligence (AGI) may be enormously important for future economic development; nevertheless, it was argued that any race for an AGI would exacerbate the dangers of an unfriendly AI. The danger of an unfriendly AGI could be reduced through a number of public policies.	√							
Evolution and control of artificial superintelligence (ASI): a management perspective	Narain *et al.* 2019	This paper contributed to the emerging area of "Artificial SuperIntelligence" The technology diffusion model was used to build a model. Any future threat stemming from ASI can be pre-empted by some long-term social measures and laws.	√							
IoT and AI for Smart Government: A Research Agenda	Kankanhalli *et al.* 2019	Presentation of main challenges facing the adoption of IoT and AI and their integration. Proposed a Research Framework for IoT-enabled AI Systems for Smart Government which included also included data analytics, aggregation and processing (part of Data Management)	√							

Table 2-6: Summary of Main Related Studies - continued

Title	Author(s)	Summary / Main finding(s)	Definition & Literature	Linkages with Variables						
				OC	DM	SQ	DOC	AU	OP	ITCU
Transforming the communication between citizens and government through AI-guided chatbots	Androutsopoulou *et al.*, 2019	The research presented how chatbots, in combination with NLP, ML and data mining technologies, yielded in developing a new 'richer' and more intelligent digital channel of communication between citizens and government.	√							
Implementing Artificial Intelligence in the United Arab Emirates Healthcare Sector: An Extended Technology Acceptance Model	Alhashmi *et al.*, 2019	This paper developed and tested through a quantitative approach and using a survey a modified Technology Acceptance Model (TAM) to explore critical success factors (CSFs) for the adoption of AI in the healthcare sector in the UAE. The study assisted in identifying Actual Usage items	√					√		
AI Watch: Defining Artificial Intelligence 2.0	Samoili *et al.* , 2020	This report proposes an operational definition of artificial intelligence in the context of AI Watch, and monitoring of AI development and implementation in Europe	√							
The Technology–Organization–Environment Framework	Baker, 2011	A chapter that describes the Technology–Organization–Environment (TOE) Framework, its description and constructs.	√							

Table 2-6: Summary of Main Related Studies - continued

Title	Author(s)	Summary / Main finding(s)	Definition & Literature	Linkages with Variables						
				OC	DM	SQ	DOC	AU	OP	ITCU
A Trust Framework for Government Use of Artificial Intelligence and Automated Decision Making	Andrews, 2022	A paper identifying current challenges of the mechanisation, digitisation and automation of public sector systems and processes in Australia. Proposed A modern and practical framework to ensure and assure ethical and high veracity Artificial Intelligence (AI) and/or Automated Decision Making (ADM) systems in public institutions.	√							
Implications of the use of artificial intelligence in public governance: A systematic literature review and a research agenda	Zuiderwijk *et al.*, 2022	A qualitative study that has identified benefits of AI use in public sector, in addition to its public governance implications	√							
A systematic literature review on the impact of artificial intelligence on workplace outcomes: A multi-process perspective	Pereira *et al.*, 2023	This study is a systematic review that explored the relationship between AI and workplace outcomes from HR and organizational perspectives and the nature of AI influences at work. This study assisted in identifying OP items.	√						√	

2.4 ORIGINALITY OF RESEARCH AND CONTRIBUTION

This research contributes to our understanding of impact of technological and organizational factors on the adoption and use of AI technologies in public sector organizations and particularly in understanding the influence on the intention to continue using such technologies. This contribution was achieved through reviewing and integrating the literature from different disciplines; AI technologies, technology adoption theories, and organizational culture to examine the factors influencing the intention to continue usage of AI technologies in public sector organizations.

In summary, there are studies that discusses AI technologies from different perspectives; AI history and definition (Haenlein & Kaplan, 2019; Gesk & Leyer, 2022; Galloway & Swiatek, 2018; Kuziemski & Misuraca, 2020; Desouza *et al.*, 2020: Dwivedi *et al.*, 2019), AI challenges (Dwivedi *et al.*, 2019; Desouza *et al.*, 2020; Sun & Medaglia, 2019; Androutsopoulou *et al.*, 2019; Suksi, 2020; Liu *et al.*, 2019), AI and other technologies (Mikalef and Gupta, 2021; Mikalef *et al.*, 2019; Ma *et al.*, 2018; Kuziemski & Misuraca, 2020; Naudé & Dimitri, 2020; Narain *et al.* 2019; Kankanhalli *et al.* 2019; Androutsopoulou *et al.*, 2019), and AI adoption in the UAE (Alhashmi *et al.*, 2019; Al Badi *et al.*, 2022; Halaweh, 2018).

Furthermore, relating to this area of research, some studies covered IS adoption models/ theories (Delone and Mclean, 2003; Petter *et al.* 2013; Davidson *et al.*, 2020; Bravo *et al.*, 2016; Mustafa *et al.*, 2020; Ching & Maarof, 2021; Al Dholay *et al.*, 2018; Yadegaridehkordi *et al.*, 2020; Mikalef *et al.*, 2019; Abdul Rahman *et. al.*, 2019; Hong *et al.*, 2006; Sun & Medaglia, 2019; Valle-Cruz *et al.*, 2020), AI adoption in Public Sector (Wirtz *et al.*, 2019; Noordt & Misuraca, 2022; Zuiderwijk *et al.*, 2022; Zhang *et al.*, 2021), AI driven government from leadership traits perspective (Almarzooqi, 2019), in addition to organizational culture (Denison, 1990; Denison *et al.* 2006; Fey and Denison, 2003; Fountaine *et al.*, 2019) and digital organizational culture (Martínez-Caro *et al.*, 2020).

Moreover, there is a gap in the literature regarding the adoption of AI technologies in public sector organizations, which requires further research. Several researchers argued that the research on AI adoption in organizations is still ascent and there is an increasing interest in this area of study (Sun & Medaglia, 2019; Valle-Cruz *et al.*, 2020), In addition Melitski *et al.*, (2010) examined the influence of organizational culture using the Denison model (1990) on the intention to adopt technology in public organizations, and concluded that there is a relation between the organizational culture and the employees' intention to use technology in the organization. Nevertheless, there is very little empirical research that studies factors influencing AI technologies adoption in public sector organisations from organizational perspective. Accordingly, the area of AI adoption and intention to continue usage in public sector organizations has not been thoroughly explored. Thus, although few studies concerning AI technology adoption have been conducted in information and communication systems (ICT), organisational culture, and organizational performance, but to date there is no one comprehensive study conducted and covering all these different disciplines.

Consequently, there is a scarcity of empirical studies on the research gap and the question of "*What is the impact of organizational constructs on the intention to continue adoption of Artificial Intelligence in Public Sector Organizations in the United Arab Emirates?*" The focus of this research will be on the identifying the factors affecting/influencing the intention to continue using AI technologies in the public sector organizations in the United Arab Emirates. The study will contribute to the existing knowledge and literature by aligning technological and organizational factors to the actual usage of AI related technologies, organizational performance, and intention to continue usage. Specifically, it will provide a conceptual model for adoption of AI technologies in public sector organizations, which includes the factors influencing intention to continue usage of AI technologies in public sector organizations.

Accordingly, through the increasing interest in adoption of AI technologies among governments worldwide to enhance it is services and citizens value offering, the new proposed conceptual model will assist decision makers, ICT professionals and AI technologies users in public sector organizations explore approaches and methods to capitalise on their resources, manage their data, and instil both an organizational and digital cultures that support the successful usage of AI technologies. This research will contribute and benefit both academics and practitioners.

2.5 CONCLUSION

In this chapter an extensive review of the existing literature, which intended to give a better understanding of the current knowledge, definitions and concepts related to AI, in addition to discussing selected IS adoption theories, and the main adoption challenges facing entities especially public sector organizations.

These reviews helped this study to identify a gap in literature, and thus to recommend the need for a more concentrated focus on the factors influencing the intention of public sector organizations to continue adopting and using AI related technologies, which would offer more insight into the question of "*What is the impact of organizational constructs on the intention to continue adoption of Artificial Intelligence in Public Sector Organizations in the United Arab Emirates*?".

To conclude, the existing literature reviewed in this chapter helped in refining the research question and objectives, identifying potential research possibilities that have not been tackled to date, building a proposed theoretical framework. In addition, the literature review will provide insights into methods, approaches, and strategies that may be suitable for conducting the study. The next chapter discusses the proposed theoretical framework for this research.

In chapter 3, the research methodology and design are discussed in details.

CHAPTER THREE: THE PROPOSED THEORETICAL FRAMEWORK

3.1 INTRODUCTION

This chapter aims at presenting the theoretical framework based on the literature review conducted in chapter 2. Grant & Osanaloo (2014) likened the theoretical framework to the "blueprint" of a house, which helps in shaping the vision, and organizing the structure and flow of the study. Therefore, the proposed theoretical framework will assist in setting the research methodologies that will be adopted, in defining main research constructs, and in building the conceptual model and findings of the study later on.

This chapter starts with presenting the integration of theories to form the main skeleton of the theoretical framework, followed by identification of the eight constructs, and presenting a visual exemplification of the proposed structure.

3.2 INTEGRATING THE THEORETICAL FRAMEWORK

3.2.1 The Hybrid Model

To conduct this research, it is necessary to develop a theoretical framework that will direct the choice of research methods and conduct the research in a manner that is consistent with the proposed theoretical framework. As a result, the use of a theoretical framework was critical in guiding the entire research study process.

Researchers have searched for parameters or factors that affect the success of IS in organisations. A single theory is not sufficient to explain the adoption process systematically, hence the decision in this study to integrate two approaches, DM IS Success Model, and the T.O.E. Framework. The two technology adoption theories are used and integrated together to form a hybrid model for examining the variables affecting the intention to continue usage of AI technologies in public sector organisations. Those two theories are the updated DM IS Success Model (2013), in addition to Technology-Organisation-Environment (T.O.E.) Framework. Figure (3-1) shows the integration between the two theories.

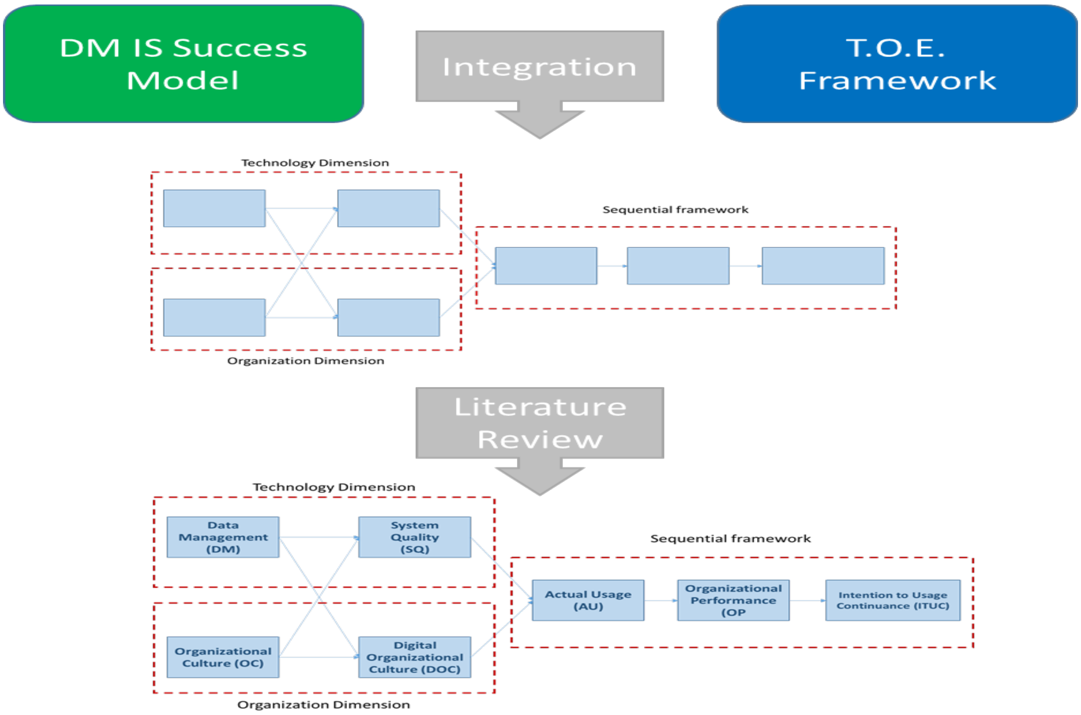

Figure (3-1) New Hybrid Model

While looking at the proposed theoretical model presented in (Figure 3-1), it indicates the three key parts that build the framework; the Technology dimension, the Organisation dimension, then a sequential framework which shows the sequential relationships between relevant dependent and independent variables. Noteworthy, the model will cover only the technology and organisation perspectives in the T.O.E. framework due to the focus on internal perspectives within the organisation, therefore no constructs under environment perspective were adopted.

3.2.2 The Proposed Constructs

The literature review conducted resulted in building a set of variables which were identified from the enablers, challenges, or opportunities that could affect the adoption of AI related technologies in organisations, for example facilitative leadership, data management, stakeholder collaborations, skills and competencies, IT infrastructure, AI governance, organisational culture, digital organisational culture, integration with other technologies as shown in Table (3-1).

Table 3-1: Supporting article for literature review proposed independent variables

Proposed Variable	**Main Supporting Article(s)**
Leadership (facilitative)	Mikhaylov *et al.* (2018); Eom *et al.* (2016)
Data management	Desouza *et al.*, 2020; Mikhaylov *et al.*, 2018; Janssen *et al.*, (2020); Löfgren *et al.* 2020; Pencheva *et al.* (2020); Sun & Medaglia (2019); Dwevidi *et al.* (2019); Liu *et al.* (2019)
Stakeholders collaborations	Desouza *et al.* (2020); Sun & Medaglia, (2019)
Skills and competencies	Mikhaylov *et al.* (2018); Marget & Dorobantu (2019)
IT infrastructure	Sun & Medaglia (2019); Dwevidi *et al.* (2019); Schedler *et al.* (2019); Marget & Dorobantu (2019)
AI Governance	Sun & Medaglia (2019); Dwevidi *et al.*, 2019; Susk (2020); Liu *et al.* (2019); Marget & Dorobantu (2019); Cruz *et al.* (2020); Janseen *et al.* (2020)
Organisational Culture	Fountaine *et al.* (2019); Mikhaylov *et al.* (2018)
Digital Organisational Culture	Martinez-Caro *et al.* (2020)
Integration with other technologies	Schedler *et al.* (2019); Tang & Ho, (2019); Zekić-Sušac *et al.* (2020); Kankanhalli, *et al.*, 2019; Lytras & Erban (2020); Ma *et al.* (2018); Chatterjee *et al.* (2018)

Each of those variables consists of different factors that influence the adoption of Artificial Intelligence related technologies.

- Visionary leadership: The essential role of leadership in using AI stems from their commitment and involvement in the organisation's operating model. There are different factors that can influence the role of leadership:
    - Facilitative Leadership: Leadership is responsible for facilitating the internal and external usage of AI in their organisation. Internally, through their commitment to provide for the needed resources, ensure needed infrastructure and processes are available, and reinforce an organisational culture that supports the adoption and implementation of AI, and externally,

through building collaborations with external stakeholders and encouraging integration and compatibility, in addition to promotion of shared vision and win-win value added cooperation.

    - AI Strategy: The organisation's management leads the vision, including setting strategic objectives that include AI objectives, which are detailed in an AI Strategy for the organisation, which is needed to align the organisational efforts and draw a roadmap for the organisation in its journey to adopt AI.
    - Processes: The management's role is to ensure that needed processes to adopt AI is developed and implemented.
- Data management: Data is considered as a critical component in AI, therefore, the management of following functions is important to the adoption and usage of AI related technologies:
    - Data creation
    - Data storage
    - Data collection
    - Data analysis
    - Data access
    - Data sharing
- Stakeholder collaborations: Public sector organisations interact with different stakeholders to provide fulfill their mandate. As per the literature review, adoption and usage of AI in public sector requires collaboration with different stakeholders to enable the organisation to deliver. This collaboration can take one or more of the following form, collaboration with:
    - Other public sector organisations
    - Private sector
    - Academia
    - Users
    - Society
- Skills and competencies: Adoption and implementation of AI and its technologies require employees to acquire/develop certain skill sets like programming, and data analysis. The factors affecting skills and competencies are:
    - Availability of required skills and competencies

    - Development of required skills and competencies
- IT infrastructure: The degree of sophistication of IT in the organisation and the readiness of IT infrastructure to cope with AI technologies requirements from computational power, databases, networks and access to data. The factors affecting IT infrastructure are:
    - Availability of IT suitable infrastructure (Hardware and software)
    - Readiness of IT infrastructure for AI
    - IS infrastructure Compatibility
- AI governance: There is a need to govern AI and ensure ethical practices and technologies. This mandates organisations to have clear regulations and policies, clear roles responsibilities for the different stakeholders, in addition to adequate controls to safeguard the interests of the citizens and their needs. The factors for AI governance are:
    - Adoption and implementation of regulations and policies
    - Setting clear roles and responsibilities for
    - Setting up adequate controls and accountability
- Organisational culture: Building a supporting organisational culture across all levels in the organisation to reinforce the change, accept AI adoption and overcome or minimize any resistance to change. Factors affecting organisational culture:
    - Role model and facilitative leaders
    - Accountability
    - Offering incentives and motivational rewards
    - Tracking and monitoring AI Progress, results and benefits
    - Educating all levels in the organisation
- Integration with other technologies: The adoption of AI in organisations can be looked at from different perspectives; first, it can be under umbrella initiative such as smart government, or on its own, another perspective is the integration of AI with other technologies, e.g. IoT, Big Data and others. The factors for integration with other technologies are:
    - Integrated under smart government initiatives
    - Integrated with other technologies

Initial proposed constructs were compared with previously reviewed studies, and constructs which were quantitatively studied through surveys were selected, then distributed under the three blocks of the proposed theoretical hybrid model in this study.

The proposed framework involved seven constructs with dependability relationships that would influence the intention to continue usage of AI technologies. The used constructs are defined while taking the context of this study into consideration, Table (3-2) lists the constructs and their definitions and sources.

Table 3-2: Constructs definition for this study

Construct	**Definition**	**Source(s)**
Data Management (DM)	*A group of activities relating to the planning, development, implementation, and administration of systems for the acquisition, storage, security, retrieval, dissemination, archiving and disposal of data*	(Office of the Deputy Prime Minister, 2005)
Organisational Culture (OC)	*Set of beliefs, values, and assumptions that are shared by members of an* organisation*, thus it helps define what is important to the* organisation *and directs all stakeholders towards achieving these important goals.*	(Barney, 1986; Kerr & Slocum, 2005)
System Quality (SQ)	*Desirable characteristics of an Information System (IS), and can be measured by different measured such as ease of use,*	(Petter *et al.* 2013; Delone & McLean 2003)
Digital Organisational Culture (DOC)	*A set of shared assumptions and understanding about organisation functioning in a digital context.*	(Deshpande & Webster's, 1989; Martínez-Caro *et al.*, 2020)
Actual Usage (AU)	*Degree and manner in which staff and customers utilize the capabilities of an Information System (IS), and some examples of the measured used for use of Information System; amount of use, frequency of use, nature of use, extent of use.*	(Petter *et al.* 2013; Delone & McLean 2003)
Organisational Performance (OP)	*The* organisation*'s ability to attain its goals or achieve its goals and objectives by using resources in an efficient and effective manner.*	(Daft, 2000); Richardo & Wade, 2001)
Intention to Continue Usage (ITCU)	*The persistent use of an ICT beyond its first use, that is, the continuous employment of a technology on a regular basis. It refers to expected future consumption or usage of an ICT and are closely related with actual usage.*	(Hernandez-Ortega *et al.*, 2014; Bhattacherjee, A., 2001)

Introducing the framework to guide the selection of the research design and data analysis outlined in the following chapters required all seven constructs of the study to be tightly related, as well as interconnected. It was also necessary to include a conceptual framework that can visualize the research constructs and aid in the development of study hypotheses, as shown in Figure 3-2 below.

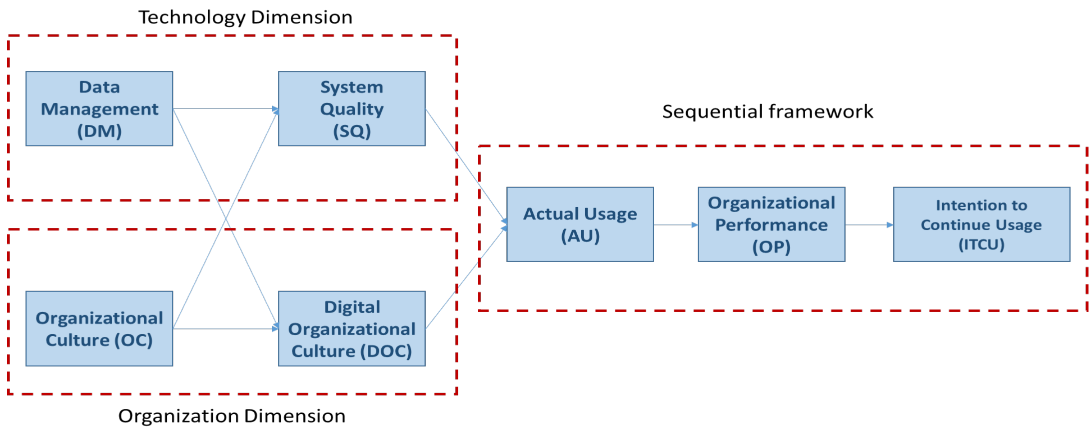

Figure 3-2: Proposed conceptual framework for this research

3.3 PART 1: THE TECHNOLOGY DIMENSION

This part of the conceptual framework illustrated the technology dimension, which is comprised of two constructs; Data Management, and System Quality.

3.3.1 Independent Construct: Data Management

Based on the literature review conducted; data management (DM) is a technology independent construct that is as per the definition in Table (3-1) above, involves the activities related to data from planning development and implementation of relevant systems to the acquisition, storage, security, retrieval, dissemination, archiving and disposal of data.

3.3.2 Dependent Construct: System Quality

System Quality (SQ) is a technology dependent construct that is adopted from DM IS Success Model (2013), it covers the desirable characteristics of an Information System (IS), and can be measured by different measures such as ease of use, reliability, user- friendliness, efficiency, and usability.

System Quality in this theoretical framework relies on two independent variables, which are proper management of data, and strong organisational culture that supports adoption of new AI technologies.

3.4 PART 2: THE ORGANISATION DIMENSION

3.4.1 Independent Construct: **Organisation*al Culture***

Organisational culture (OC) is an organisation independent construct, where in this study Denison organisational culture framework was adopted. In this model as per Denison et al (2006) there are four traits for organisational culture; involvement, consistency, adaptability, and mission, with set of measures for each trait.

3.4.2 Dependent Construct: Digital Organisational Culture

Digital organisational culture (DOC) is an organisation dependent construct that is adopted from the literature review, it covers the collaboration of teams within the organisation, orientation towards digital technology changes, adoption of a culture of innovation, and finally the adoption of a digital strategy and sharing it with the organisation's internal stakeholders (Martínez-Caro *et al.*, 2020).

Digital organisational culture in this theoretical framework relies on proper management of data, in addition to on strong organisational culture that supports adoption of new AI technologies.

3.5 PART 3: THE SEQUENTIAL FRAMEWORK

3.5.1 Dependent Construct: Actual Usage

Actual Usage is considered in the proposed theoretical framework as a dependent variable that depends on both System Quality and Digital Organisational Culture constructs. Actual Usage is adopted from DM IS Success Model (2013) and is described in terms of frequency of use, and amount of use (Kim *et al.*, 2007; Klopping & Mckinney, 2004).

3.5.2 Dependent Construct: **Organisation*al Performance***

Organisational Performance is treated in the proposed framework as a dependent variable that relies on Actual Usage of AI technologies in the organisation. Organisational performance is derived from "Net benefits" construct in DM IS Success Model (2013), and is measured in terms of more accurate data, internal and external satisfaction, improvements in financial, operational and business processes (Yadegaridehkordi *et al.*, 2020; Mikalef *et al.*, 2019; Wamba *et al.*, 2019)

3.5.3 Dependent Construct: Intention to Continue Usage

Intention to continue usage of AI technologies is a dependent construct in the sequential framework construct that is adopted from the literature review, it covers the organisation's intention to continue using AI, plan to continue using AI technologies (Yadegaridehkordi *et al.*, 2020; Maduku *et al.*, 2016) based on the organisation's performance.

3.6 CONCLUSION

This chapter summarised the theoretical framework used in this study, which is a blueprint guiding the following steps in conducting this research, for example the research methodology in Chapter 4.

Based on literature review, this theoretical framework consisted of three parts with seven constructs distributed over the framework; technology part, organisation part, and the sequential framework. The intention to continue using AI related technologies in the organisation is subject to a sequential dependency relationships, and the relationships between the constructs are illustrated in terms of a set of hypotheses in Chapter 5.

CHAPTER FOUR: RESEARCH METHODOLOGY

4.1 INTRODUCTION

In previous chapters, the research question and research objectives were set, and then review of the existing literature was conducted to get a better understanding of research question. The purpose of this chapter is to describe the proposed research methodology for this study, which leads to answering the research question and meeting the objectives set out in the research question, as well as clarifying the reasons for this choice.

This research methodology outlines the underlying research philosophical stance, the applied research approach, the chosen research design, which includes the research strategy, the quantitative data collection method, the sampling strategy and criteria for inclusion, as well as a brief on data analysis tools to be used. Figure (4-1) shows the interconnection between research philosophy, research approach, designs and research methods

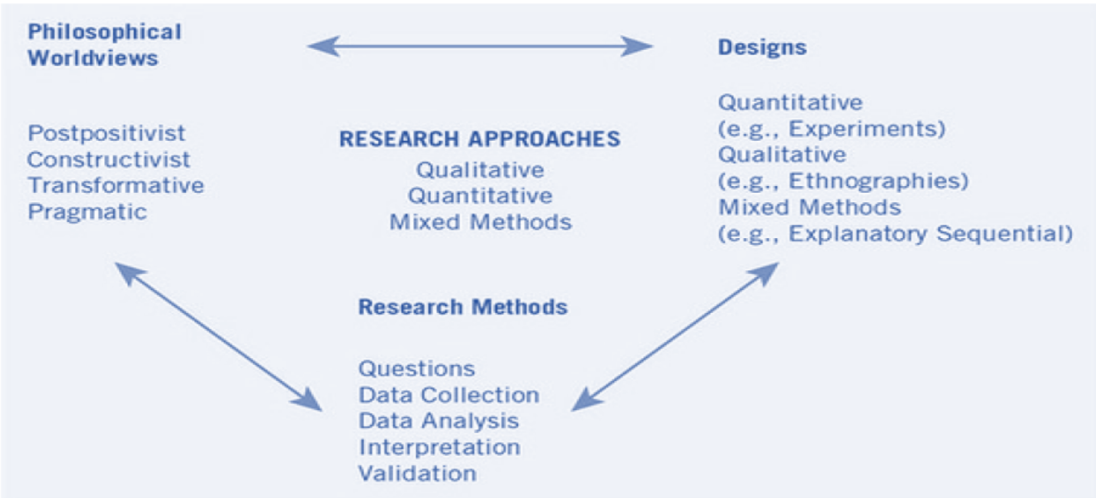

Figure 4-1 Interconnection between Research Philosophy, Research Approach, Designs and Research Methods from Creswell & Creswell (2018, p. 43)

4.2 RESEARCH PHILOSOPHY

Saunders *et al.*, (2019) considered research philosophy in principle as the system of researcher's beliefs and assumptions adopted in relation to knowledge development and its nature in relation to a research. Therefore, it is critical to understand both the researcher's own philosophical position, and the philosophical factors that would lead to reach satisfactory research outcomes, due to the following reasons; First, researcher's obligation to understand the issues related to creating knowledge (epistemology) and researcher's own reflexive role in the research project. Second, this understanding will help in the research design process to provide answers for the research question(s). Third, recognizing the appropriate workable research design, for example, qualitative, quantitative, or mixed methods. Fourth, this will help in adapting the research design to cope with the research constraints (Easterby-Smith *et al*., 2015).

There is no one "best" philosophy in business and management research, Saunders *et al.,* (2019) discussed five major research philosophies that are applicable to business and management researches; positivism, interpretivism, pragmatism, critical realism, and postmodernism. Following is a brief discussion of two of those philosophies, then a general comparison based on ontology, espistemology, axiology, and typical methods used.

4.2.1 Positivism:

In general, positivism is the most widely used approach in social science (Neuman, 2014). It can be defined as "*an organised method for combining deductive logic with precise empirical observations of individual behaviour in order to discover and confirm a set of probabilistic causal laws that can be used to predict general patterns of human activity*" (Neuman, 2014).

To develop research hypotheses statements, positivist researchers can use existing theory or literature. These hypotheses provide hypothetical explanations based on gathered facts, which can be tested and confirmed, either fully or partially, or refuted, leading to further development of theory, which can then be tested by further research (Saunders *et al*., 2019). The positivist paradigm has a tendency of usig quantitative data and statistical analysis (Collis & Hussey, 2009), and the research is would try to be detached from the research and neutral without influencing the outcomes and findings of the research (Saunders *et al*., 2019)

4.2.2 Interpretivism:

Interpretivisim, focuses on studying the meanings created by humans as they are different from their physical phenomena, this would lead to creating newer and richer understanding of social works, and from business context, this means looking at organizations from the perspective of humans (managers, employees, and others) (Saunders *et al*., 2019). Interpretivism has a tendency of using qualitative data, and interpretative explanations over causal forms (Newman, 2014). In summary, in focuses on *understanding* of what is happening in the research problem or given context, it considers multiple realities, several participants' perspectives, the researcher involvement, taking into consideration the contexts of the research context, in addition to contextual understanding and interpretation of collected data (Carson *et al.*, 2001, p. 6). A comparison between these main philosophical stances is presented in Table (4-1) below.

Table 4-1: Camparison of Research Philosophies (Positivism – Interpretivism – Pragmatism) adopted from Saunders *et al.* (2019, p. 144)

Ontology (nature of reality or being)	**Epistemology** (what constitutes acceptable knowledge)	**Axiology** (role of values)	**Typical methods**
	Positivism		
Real, external, independent One true reality (universalism) Granular (things) Ordered	Scientific method Observable and measurable facts Law-like generalisations Numbers Causal explanation and prediction as contribution	Value-free research Researcher is detached, neutral and independent of what is researched Researcher maintains objective stance	Typically deductive, highly structured, large samples, measurement, typically quantitative methods of analysis, but a range of data can be analysed
	Interpretivism		
Complex, rich Socially constructed through culture and language Multiple meanings, interpretations, realities Flux of processes, experiences, practices	Theories and concepts too simplistic Focus on narratives, stories, perceptions and interpretations New understandings and worldviews as contribution	Value-bound research Researchers are part of what is researched, subjective Researcher interpretations key to contribution Researcher reflexive	Typically inductive. Small samples, in-depth investigations, qualitative methods of analysis, but a range of data can be interpreted
	Pragmatism		
Complex, rich, external 'Reality' is the practical consequences of ideas Flux of processes, experiences and practices	Practical meaning of knowledge in specific contexts 'True' theories and knowledge are those that enable successful action Focus on problems, practices and relevance Problem solving and informed future practice as contribution	Value-driven research Research initiated and sustained by researcher's doubts and beliefs Researcher reflexive	Following research problem and research question Range of methods: mixed, multiple, qualitative, quantitative, action research Emphasis on practical solutions and outcomes

The decision to use one philosophical paradigm over the other is a significant task. There are several concerns that drive this decision, which are categorized into first, researcher concerns: The researcher's perspective based on his own beliefs and values. Second: the research concerns, which are relevant to the research questions and set objectives, to the degree of flexibility or rigidness of the research, to the problem definition and understanding, then to the generalisability of the results, and finally, the usefulness of the findings (Patton, 2009).

The aim of this research project is to identify the dependent and independent constructs that affect the usage and intentions to continue using Artificial Intelligence related technologies in public sector organizations in United Arab Emirates. The conducted literature review referred to six main Information System technology adoption theories. Those theories are classified based on the context of use into individual level theories (e.g. TAM, and UTAUT), and organizational level theories (e.g. TOE, DOI, TEF, and updated DM IS Success Model). Some of the identified theories have been applied in similar contexts of public sector in areas of smart government (Kankanhalli *et al.*, 2019: Schedler *et al.*, 2019), public mobile applications (Schedler *et al.*, 2019; Hong *et al.*, 2006) or IoT (Ma *et al.*, 2018; Tang & Ho, 2019; Zekić-Sušac *et al.*, 2020). However, none of the studies reviewed, used any of the existing technology adoption models in the context proposed in this research to study Artificial Intelligence usage and intention to continue using it in the public sector in the United Arab Emirates.

Consequently, using the positivism paradigm will help to investigate the constructs proposed in the technology adoption model(s) that have positive impact on the success of AI adoption in organization, can collect larger volume of data, explain the causal relationship in results and will help in the generalization of the findings.

Finally, within the positivism paradigm, the researcher is external and objective. The data interpretation follows standard statistical procedures, which makes the findings more reliable and valuable. Overall, using the positivism paradigm over other paradigms in this research is more suitable to answer the research questions in a justifiable manner.

4.3 RESEARCH APPROACH

The nature of each research mandates a specific research theory to be adopted, and reflected in research design. Therefore, this needs to be set and clear at the beginning of the study; the sequence of theory development and data collection steps, and which takes place prior to the other in order to design the suitable research strategy. In other words, to decide to adopt one of the two approaches: Deductive or Inductive (Saunders *et al.*, 2019). Both approaches are explained below:

Deductive approach: Deduction has its roots in natural sciences research, and in general involves the development of a theory, which can result of literature review, then rigorously testing it (Saunders *et al.*, 2019). Deduction as a process enables researchers to arrive to a reasoned conclusion by logical generalizations of a known fact (Creswell & Creswell, 2018), as shown in Figure (4-2). In general, there are five characteristics for the deductive approach: (1) the explanation of causal relationships between variables; (2) the testing of hypotheses through quantitative data collection; (3) structured approach: (4) the operationalization of variables to enable measurement of facts quantitatively; and (5) generalisation from the sample to a wider population. Saunders *et al.*, (2019) illustrated that linking the deductive approach to philosophy is more concerned with the positivistic paradigm.

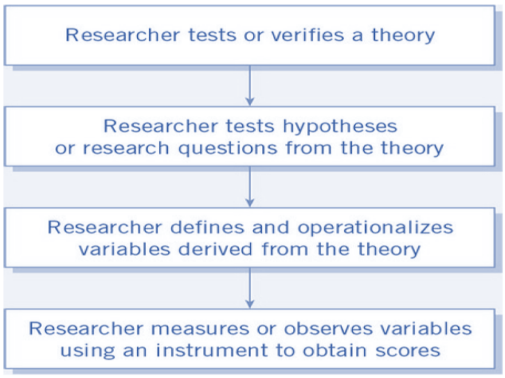

Figure 4-2: Deductive Approach in a quantitative research from Creswell & Creswell, (2018, p. 100)

The **inductive approach** is an alternative approach to building theory in backward deductive steps as shown in Figure (4-3). Researchers start from an observation to broader theories and generalizations. It is more exploratory in its nature while considering the humans' interpretation of their surrounding social world (Saunders *et al.*, 2019), and subsequently, the meaning of data (Creswell & Creswell, 2018) which gives the inductive approach its distinctive edge. Since it is more concerned with meaning and interpretation, this approach is mostly adopted by interpretivists.

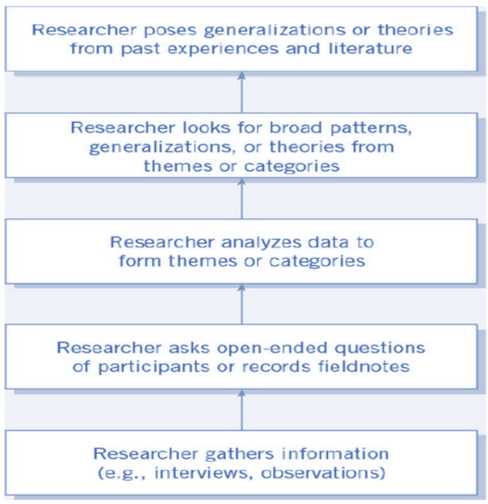

Figure 4-3: Inductive Approach in a qualitative research from Creswell & Creswell, (2018, p 100)

In the following Table (4-2), the major differences between deductive and inductive approaches are presented.

Table (4-2): Comparison of Deduction and Induction Research Approaches adopted from (Saunders *et al.,* 2019, p. 153)

	Deduction	Induction
Logic	In a deductive inference, when the premises are true, the conclusion must also be true	In an inductive inference, known premises are used to generate untested conclusions
Generalisability	Generalising from the general to the specific	Generalising from the specific to the general
Use of data	Data collection is used to evaluate propositions or hypotheses related to an existing theory	Data collection is used to explore a phenomenon, identify themes and patterns and create a conceptual framework
Theory	Theory falsification or verification	Theory generation and building

As a result of the research philosophy chosen in this study (i.e. positivism), and the characteristics of the deductive approach as outlined above, it is most appropriate to use a deductive approach to address the research question and objectives in this research.

4.4 RESEARCH DESIGN

Research design is defined as "*The general plan of how you will go about answering your research question(s)*" (Saunders *et al*., 2019, p. 173). The purpose of the research can be designed to fulfil either an explanatory (studying established relationships between constructs or variables), evaluative (How well something works), exploratory (clarification of understanding of a phenomena), descriptive purpose (profiling of situations, events or persons), or combination of these (Saunders *et al*., 2019).

Based on the research question and its objectives, in combination with the aforementioned choices, a philosophical stance was established (i.e. positivism), and the research approach (i.e. deduction); the underlying research design is explanatory in nature (i.e. quantitative methodological choice). Overall, this is because this research includes the explanation of relationships between the proposed dependent and independent constructs, rather than the exploration of new insights or description of facts or phenomena.

The subsequent sections will clarify the reasons behind choosing the research strategy and techniques, the data collection method, sampling, in addition to data analysis method.

4.5 RESEARCH STRATEGY

The research strategy guides the researcher during the different phases of the research: the planning, the executing, and the monitoring (Johannesson & Perjons, 2014). It is the bridge between the philosophical stance and the choices for data collection and analysis. The selection of the appropriate research strategy will be guided by several factors such as: the research question, and its objectives; coherence with philosophical and methodological choices; extent of available existing knowledge; resources and time needed and available; possibility of combining different strategies (Saunders, *et al*., 2019); in addition to the ethicality of the strategy followed (Johannesson & Perjons, 2014).There are various research strategies available in the literature, some of which are listed in Table (4-3) below.

Table 4-3: Main Research Strategies with linked research methodologies (from Saunders *et al*., 2019)

#	Main Research Strategy	Linked Research methodology		
		Quantitative	Quantitative	Mixed Methods
1	Survey	✓		
2	Experiment	✓		
4	Case Study	✓	✓	✓
5	Ethnography		✓	
6	Action Research		✓	
7	Grounded Theory		✓	

Each of those strategies has its purpose and fulfils different tasks, for example in an experiment strategy the researchers aim to explain hypothesis through measuring the probability of change in a variable based on the change of another. As for case studies, they focus on one instance or part of a phenomenon, and might be suitable for painting detailed picture of that instance, nonetheless, Johannesson & Perjons, (2014) noted that they might not be a suitable method for studying large population as it focuses on a part of a phenomenon. Whereas, the survey, which is associated with deductive approach, provides a bird’s view of subject understudy (Johannesson & Perjons, 2014), and allows for collection of standard data from a large sample size, in addition, surveys can be used to explain relationships between variables and formulate a model (Saunders *et al.,* 2019). Therefore, survey strategy will be applied in this research, which will be explained in detail and a clear reasoning is presented for choosing this strategy over the other available strategies.

Rea & Parker (2014) discussed that survey research can result in gathering data about a large amount of people, therefore it is a suitable method to collect data for theory or model testing, where examining the proposed constructs inter-relationships is needed. This often includes descriptive data, in addition to perception or attitude data on the subject under research (Johannesson & Perjons, 2014).

Saunders *et al.*, (2019) considered survey research as a popular strategy among researchers who conduct business and management studies, and best suitable for data collection on clearly-defined research areas. This is consistent with the deductive approach chosen in this research project. Furthermore, Williams *et al.*, (2015) considered that the survey strategy has demonstrated to be a suitable strategy in the field of technology models.

As for the survey data, Rea & Parker (2014) argued that it can be collected in an efficient manner and conclusions can be drawn and generalizations can be made regarding an entire population as a result of gathering data from a representative sample of the targeted population. Thus, large volume of data can be collected at a reasonable cost within a short timeframe (Saunders *et al.*, 2019). Second, the standardisation of the gathered data enables data comparison (Saunders *et al.*, 2019) and the answers of participants can be statistically compared objectively, which would enhance the generalisability of the research findings. Finally, through the use of a survey strategy and during data collection, the participants can express their attitudes and perceptions about the theoretical constructs identified in literature review by using nominal or ordinal scales such as Likert scale.

Taking all the mentioned advantages and reasons into account, the use of a survey strategy in this research is justified.

4.6 DATA COLLECTION METHOD

Johannesson & Perjons, (2014, p. 39) argued that "*While the research strategy provides useful support on a high level, it needs to be complemented with research methods that can guide the research work on a more detailed level*". There are several methods that can be used depending on context of the study, for example, experiments, observations, semi-structured, in-depth and group interviews, as well as questionnaire (Saunders *et al.*, 2019). The use of those methods varies depending on the research methodology, some of them fit more in qualitative research, whilst others are more suitable for quantitative research. Since the philosophy adopted in this research is positivism, the approach applied is deductive, and the survey strategy is used, and taking into consideration the context of targeted population, the time and cost constraints that underlies this research, consequently, the most suitable data collection method selected for this research is the self-completed questionnaires.

Data collection through questionnaires is one of the most popularly used approaches in business research (Cooper & Schindler, 2014; Saunders *et al.*, 2019). This is mainly linked to the fact, that it is considered as an efficient way of data collection and the best choice for targeting large sample size in a short period of time (Saunders *et al.*, 2019), which is the aim of the survey to target employees in the public sector organisations in the United Arab Emirates. What is more, when using standardized questions in questionnaires, standardized interpretation of the results of questionnaires for all respondents is followed, (Saunders *et al.*, 2019). In addition, drafting high quality questionnaire items will enable getting more appropriate responses through enabling the participants to get a better understanding of the questions (Neuman, 2014).

Saunders *et al.*, (2019) classified questionnaires into two types: self-completed, and researcher completed questionnaires as shown in Figure (4-4), accordingly, the way how the questionnaire is administered will affect questionnaire designing, as well as the respondents needed time to answer the questionnaire, in addition to factors related to the questionnaire such as, survey length, number and type of questions, and other factors related to sampling such as the acceptable respondents sample size (Saunders *et al.*, 2019). Thus, the mode of questionnaire chosen "*will dictate how certain you can be that the respondent is the person whom you wish to answer the questions and thus the reliability of responses*" (Saunders *et al.*, 2019. p 509).

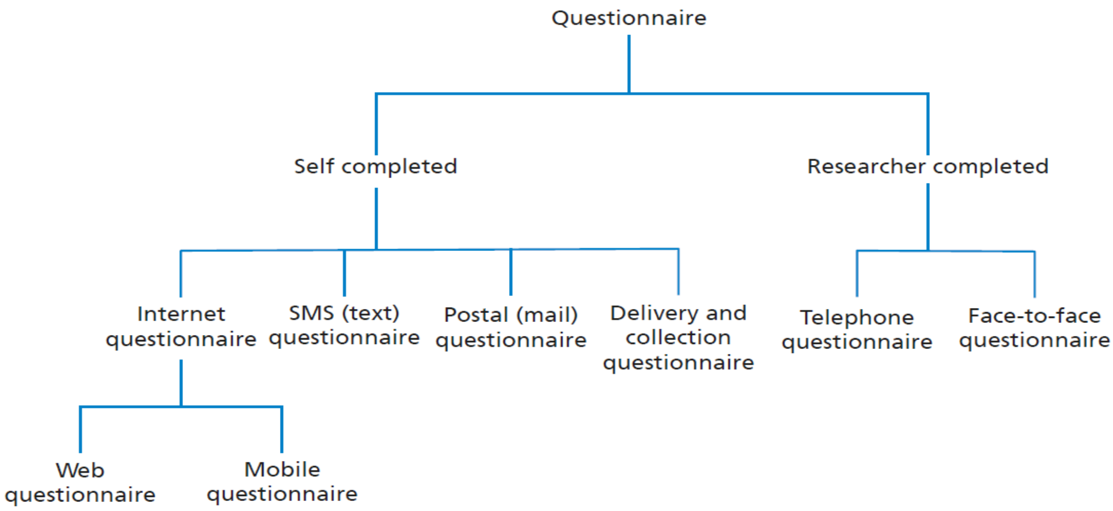

Figure 4-4: Types of Questionnaire (Saunders *et al.,* 2019, p. 506)

This research will apply self-completed web questionnaire. This is mainly linked to the advantages included. First, internet questionnaires offers the researcher to instantly reach to a large sample size simultaneously (Rea & Parker, 2014) and are usually more cost and time effective tool than other ways for example interviews, phone calls or postal. Furthermore, internet questionnaires do not impose any time constraints on respondents to complete the questionnaire. As a result, according to Dillman (2007), respondents of self-completed questionnaires are more likely to provide honest and non-socially influenced responses. Additionally, this will facilitate the data analysis as collected data can be downloaded and used directly with a statistical software, in this study SPSS, and then analysed (Saunders *et al.*, 2019). Thus, taking into account the above-mentioned features and benefits of this type of questionnaires, this data collection method is viewed to suit the needs of this study to answer the research question as well as to fulfil the research objectives.

4.6.1 Targeted Population and Sampling frame

The population as defined by Collis & Hussey (2014, p.197) is "*a body of people or collection of items under consideration for statistical purposes*". Malhotra *et al.* (2006) stated that the target population consists of several components: research-sampling unit (a subset of population), research collection data time and research extent.

The conducted literature review showed that there was scarcity in number of studies on Artificial Intelligence in the United Arab Emirates in general and in public sector organizations in specific, despite the fact that United Arab Emirates (UAE) is one of the pioneering countries in the region to adopt AI as the UAE launched its AI Strategy in 2017, whereas Qatar published its national AI Strategy in 2019, then Kingdom of Saudi Arabia announced its AI strategy in October 2020, followed by Jordan and Egypt in 2022.

Federal and local government organizations started executing the UAE National AI Strategy and adopted and implemented AI based technologies across different sectors, for example, in Education, Ministry of Education launched in 2017, its new AI based learning model "Alef" for enhancing the learning processes (WAM, 2017), in regulations and law, Abu Dhabi Judicial Department (ADJD), has launched "Justice Intelligence" project, as part of the government's Artificial Intelligence (WAM, 2017), in Healthcare, Dubai Health Authority (DHA) piloted its first fully AI fitness center, in transport and infrastructure, Roads and Transport Authority (RTA) a local Dubai government entity launched in 2018, around 75 AI and smart city projects (Almasar, 2019).

Nevertheless, the literature review identified a research gap in the studies conducted on adoption of AI related technologies in general in the public sector organizations in the United Arab Emirates, and on the intentions to continue using AI related technologies in specific. To bridge this gap, and contribute to the existing body of knowledge, this thesis is targeting public sector organizations in the United Arab Emirates to examine variables impacting the intentions to continue using AI related technologies in those organizations.

In this research, the targeted population is the public sector organizations in the United Arab Emirates, which comprises of federal government and local governments in the seven emirates. Charity organizations in addition to sub-organizations which are part of larger organizations were excluded. Organizations were listed from the official websites of federal and local governments in the United Arab Emirates.

Table 4-5: The UAE federal and local government entities sources as on 01 February 2022.

#	Organization Type	Source
1	The UAE federal government	https://uaecabinet.ae/en/federal-government-entities
2	Abu Dhabi Government	https://www.tamm.abudhabi/en/abu-dhabi-government-entities
3	Dubai Government	https://grpportal.dubai.gov.ae/en/AboutGRP/Connected/Pages/default.aspx
4	Sharjah Government	https://ec.shj.ae/en/government-entities/

Table 4-5: The UAE federal and local government entities sources as on 01 February 2022 (contd.)

5	Ajman Government	https://www.ajman.ae/en/entities
6	Umm Al Quwain Government	https://www.uaq.ae/en/umm-al-quwain/department.html
7	Ras Al Khaimah Government	https://www.rak.ae/wps/portal/rak/government-entities
8	Fujairah Government	https://fujairah.ae/en/pages/fujairah_government.aspx

According to Churchill & Brown (2004), the sampling frame provides a list of sampling units, from which a sample will be drawn, whereas Collis & Hussey (2014, p.197) defined sample frame as "*a record of the population from which a sample can be drawn*", and it helps in identifying the number of items in the targeted population.

4.6.2 Sampling technique:

This section describes the sampling method used in this positivist-philosophy research for selecting survey participants. In general, sampling techniques equip the researcher with methods that enable him to optimise the volume of needed data to collect by considering data from a sample, rather than the whole population or possible cases (Saunders *et al.,* 2020). In this study, there are two common sampling techniques that suit the research philosophy, which are: probability-sample technique and non-probability-sampling technique (Easterby-Smith *et al.*, 2012; Saunders *et al.*, 2019; Creswell, 2014), as shown in Figure (4-6).

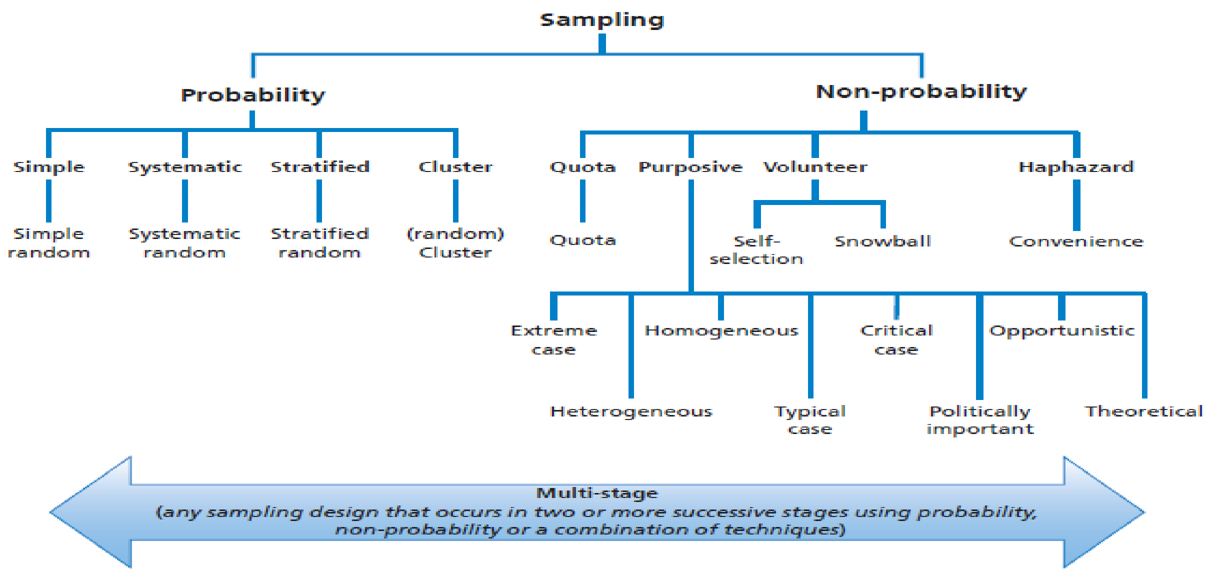

Figure (4-6): Sampling Techniques (Saunders *et al.,* 2019, p. 297)

Saunders *et al.* (2019) noted that probability-sample technique describes forms of sampling design where the probability of each entity being part of the sample is known. Whereas, non-probability-sampling technique describes form of sampling where the likelihood of each population entity being include in the sample cannot be known. Therefore, a probability sample is one in which the items of the sample are chosen on the basis of known probabilities', while the non-probability sample is one in which the participants included are chosen without regard to their probability of being selected (Berenson & David, 1999; Creswell, 2014). Consequently, for non-probability samples, it is not possible to generalize the results based on inferences from data, though Saunders *et al.,* (2019), argued that there is a possibility to generalize but not on statistical bases.

Table 4-6: Impact of Various Non-Probability Sampling Techniques (from Saunders *et al.*, 2019, p. 318)

Group	Technique	Likelihood of sample being representative	Types of research in which useful	Relative costs	Control over sample contents
Quota	Quota	Reasonable to high, although dependent on selection of quota variables	Where costs constrained or data needed very quickly so an alternative to probability sampling needed	Moderately high to reasonable	Specifies quota criteria
Purposive	Extreme case	Low	Unusual or special to offer more revealing insights to explain the more typical	Reasonable	Specifies what is unusual or extreme
	Heterogeneous	Low, although dependent on researcher's choices	Reveal/illuminate key themes	Reasonable	Specifies criteria for maximum diversity
	Homogeneous	Low	In-depth exploration and reveal minor differences	Reasonable	Specifies criteria to identify particular group
	Typical case	Low, although dependent on researcher's choices	Illustrative	Reasonable	Specifies what is 'normal'
	Critical case	Low	Where focus is on importance	Reasonable	Specifies criteria as to what is important
	Politically important	Low	Where focus is on salience and connections	Reasonable	Specifies criteria re political importance
	Opportunistic	Low	Where unexpected occurs during research	Reasonable	Recognises and decides whether to take opportunity
	Theoretical	Low	Inform emerging theory	Reasonable	Specifies where to select initial participants and subsequent choice to inform emerging theory
Volunteer	Snowball	Low, but cases likely to have characteristics desired	Where cases difficult to identify	Reasonable	Selects only initial participant
	Self-selection	Low, as cases self-selected	Where access difficult, research exploratory	Reasonable	Offers general invitation
Haphazard	Convenience	Very low (often lacks credibility)	Ease of access	Low	Haphazard

There are several factors affecting the decision to select a sampling technique. First, the nature of this research as it is targeting a population of decision makers, managers, IT professionals and employees who are using AI technologies in public sector organizations in the United Arab Emirates. Second, the requirement of research questions and its objectives. Third, it is very challenging to reach out to public sector organizations and start collecting data from the entire government entities due to some restrictions of access and available time. Moreover, there is a lack of access to comprehensive, reliable, and clear data about AI adoption in the public sector organizations in the United Arab Emirates, therefore, a combination of *non-probability sampling* techniques were used, thus the targeted sample was selected in a non-random manner. Figure (4-7) shows a flowchart with actions for choosing a non-probability sampling technique as per Saunders *et al*., (2019).

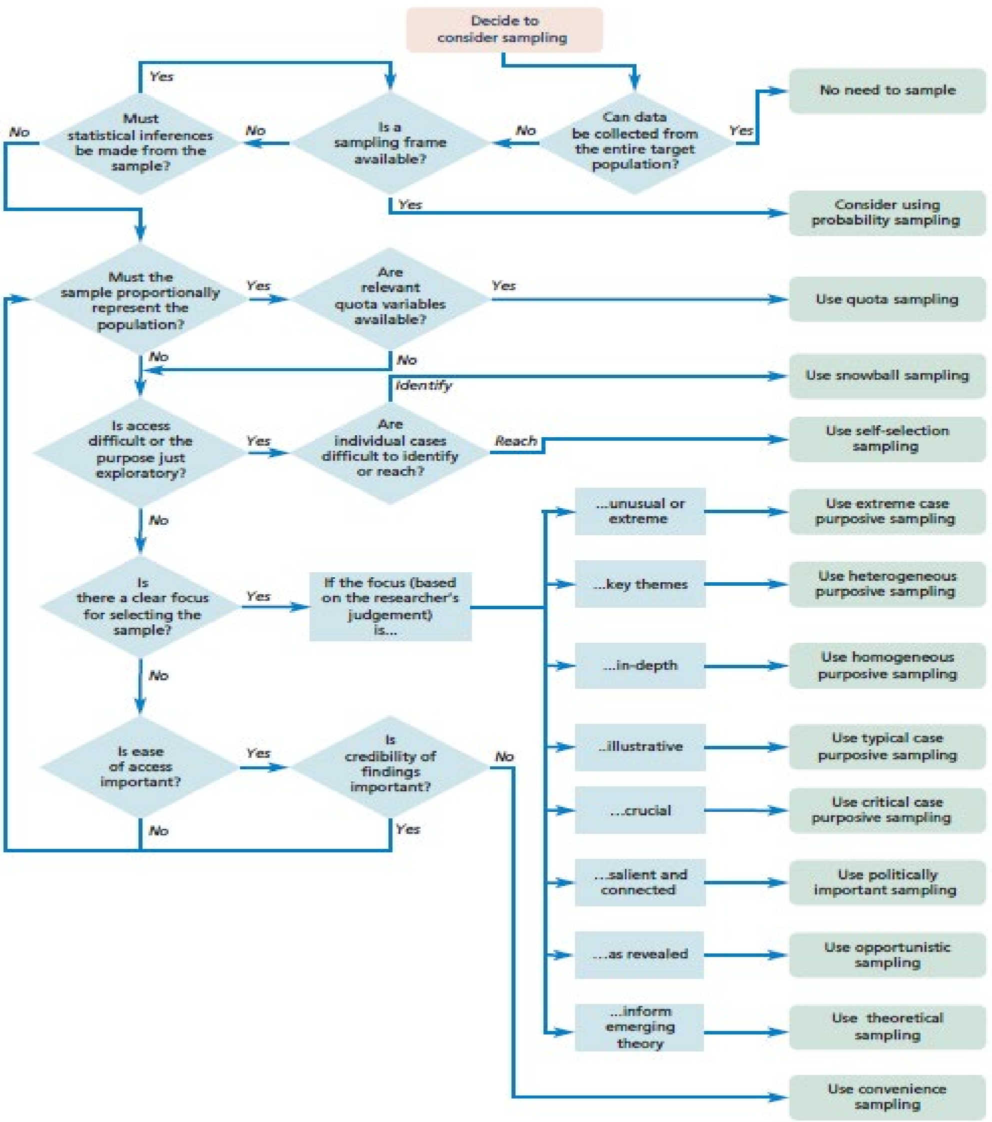

Figure (4-7): Choosing a non-probability Sampling Techniques (Saunders *et al.,* 2019, p. 316)

Due to the need to identify and reach for employees in public sector organizations in the United Arab Emirates, A combination of two sampling techniques were used in this study, the self-selection sampling and snowball sampling. *Self-selection sampling* is defined as "*a non-probability sampling technique in which the participants are allowed to identify their desire to be part of the sample and take part in the research*" (Bradley, 1999). In addition, it can be used in conjunction with other sampling techniques, such as snowball sampling, which can enable the researcher to reach out to appropriate participants to provide both of needed data and further data sources (Saunders *et al.,* 2019; Fossey *et al.,* 2002). Hence, the research applied the snowball sampling technique. Oates *et al.,* (2022) defined Snowball sampling as "*a non-probability sampling technique in which subsequent respondents are obtained from information provided by initial respondents.*" The technique is generally selected and used in the cases when it difficult to identify desired members of a population, or the process to be followed is unclear.

This study used an online questionnaire targeting decision makers, managers, ICT professionals and potential users in public sector organizations in the United Arab Emirates The potential targeted organizations and the self-selection sample received participation invitation and asking them to fill in the online questionnaire, and nominate more fellow colleagues or participants in other government organizations in the United Arab Emirates, who are interested in this study.

4.6.3 Sample Size

The sample size decision in general is influenced by several factors, such as resources availability, degree of data accuracy and reliability, available timeframe for the study, and segmentation of the respondents, in addition to the requirements of the statistical analysis method used in the study to give reliable results (DeVaus, 2002; Saunders *et al*., 2019).

Hair *et al.,* (2018) illustrated that Structural Equation Modelling (SEM), which is used in this study, is like most of other statistical analysis techniques which requires a convenient sample size to run the analysis in order to produce reliable estimates, and it is recommended by different authors to obtain a sample size greater than 200 in order to for the SEM to provide analysis results including goodness-of fit and parameter estimates with acceptable confidence levels (Hair *et al*., 2018; Boomsma & Hoogland, 2001; Kline, 2005; Gerbing & Anderson, 1993; Harris & Schaubroeck, 1990).

The official UAE government website (https://u.ae/en/about-the-uae/the-uae-government) refers to list of public sector organizations on federal and local levels. Organizations will be approached through official emails or contact numbers, and through professional networks like LinkedIn in order to get the required representative sample size and to ensure a satisfactory return rate.

4.7 DATA ANALYSIS

As previously mentioned, this study will use SEM to analyze the research data collected through the research survey. Beran & Violato, (2010) considered SEM as a powerful multivariate statistical analysis technique with flexible frameworks that enables the researcher to build relationships among the variables under-study, and then analyze and test the model.

This research comprises of study of a proposed model with a set of several constructs, and then test the relationships based on the proposed hypotheses. SEM would enable the researcher to examine the constructs that operate as independent as well as dependent construct (Hair, 2018).

4.8 CONCLUSION

Chapter 4, presented the research methodology supported with reasoning for choosing each part. This included the description of research philosophy, research approach, as well as the research design, which included the research strategy, the data collection method, and the sampling strategy, in addition to a brief overview of the multivariate statistical analysis technique; SEM.

The following Chapter 5 will present and discuss the Conceptual Model, including the constructs, their relationships and hypotheses made.

CHAPTER FIVE: CONCEPTUAL MODEL AND HYPOTHESES

5.1 INTRODUCTION

The purpose of this chapter is to introduce the conceptual model that will be used to define the main research constructs and the hypothesized relationship between the independent and dependant variables, which will be further explained later in the study. This conceptual model will provide a visual representation of the constructs that were identified through the literature review.

In chapter two, factors that affect the usage of Artificial Intelligence related technologies in Public Sector Organizations in the UAE were identified. This review included articles related to the adoption, usage and intentions to continue usage of AI, and other new technologies in government sector, in addition to literature covering various technology/information system success models.

With the research questions and objectives in mind, this chapter in its three sections summarises the main findings of the literature review. The first section discusses the main variables identified in the literature review. Whereas, section 2 presents and describes the conceptual model and the eight research hypotheses, then section three discusses variables operationalisation.

5.2 MAIN VARIABLES IN LITERATURE REVIEW

The literature review conducted in this research resulted in identifying a set of variables that would contribute to answering the research questions and meet its objectives. Those variables were used to develop the conceptual model derived from hybrid IS adoption models: System Quality (Delone & Mclean, 2003; Petter *et al.* 2013; Davidson *et al.*, 2020; Bravo *et al.*, 2016, Geebren *et al.*, 2021; Mustafa *et al.*, 2020; Chang *et al.*, 2018; Alsabawy *et al.*, 2016), and Data Management (Mikhaylov *et al.*, 2018; Mikalef and Gupta; 2021; Ransbotham *et al.*, 2018; Gangwar, 2018; DeSouza *et al.*, 2020; Janssen *et al.*, 2020; Löfgren *et al.*, 2020; Pencheva *et al.*, 2020; Sun & Medaglia, 2019; Dwevidi *et al.*, 2019; Liu *et al.*, 2019) which both fall under Technology Dimension. The Organization Dimension included Organizational Culture (Denison, 1990; Denison *et al.* 2006; Fey and Denison, 2003), and Digital Organizational Culture (Martínez-Caro *et al.*, 2020), The constructs of the two aforementioned dimensions affect the actual usage construct of AI system (Delone & McLean, 2003; Sun *et al.*, 2009; Klopping & Mckinney, 2004). The Actual Usage of the AI system is a construct that was identified to impact organizational performance (Yadegaridehkordi *et al.*, 2020; Mikalef *et al.*, 2019; Wamba *et al.*, 2019) which will impact the Intention of AI system usage continuance (Abdul Rahman et. Al., 2019; Hong *et al.*, 2006).

5.3 MODEL DEVELOPMENT AND RESEARCH HYPOTHESES

This study focuses on seven main constructs: AI System Quality, Data Management, Organizational Culture, Digital Organizational Culture, Actual Usage, Organizational Performance and Intention to Continuance Usage, which in chapter 2, a summary of their concepts and definitions was discussed.

5.3.1 Data Management (DM)

Data quality as per (Delone & McLean, 2003) is one of the items used for measuring system quality, and quality management in addition to access to diverse data sources can assure quality of data (Arnott, 2008), and the unreliable, inaccurate or poor data will affect the functionality of the system, which Petter *et al.* (2013) argued that it is one of the characteristics of system quality. Mikalef & Gupta (2021) noted that managers in organizations considered data as one of the key enablers in leveraging the potential of AI systems, and was regarded as a corporate asset. In addition, the quality of both internal and external data from stakeholders plays an important role in both of the training and learning of AI systems, and the operation of AI applications (Ransbotham *et al.*, 2018). Several researchers considered data management construct is crucial to the usage of AI in organizations. This is due to the fact that any compromise in confidentiality, security and control or the absence of data labeling or accuracy would affect the quality of the system and thus would lead to failure (Janssen *et al.*, 2020; Desouza *et al.*, 2020; Mikhaylov *et al.*, 2018; Löfgren *et al.*, 2020; Pencheva *et al.*, 2020; Sun & Medaglia, 2019; Dwevidi *et al.*, 2019; Liu *et al.*, 2019). Therefore, the management of data affects AI system quality in public sector organizations.

H1a Data Management impacts positively the AI System Quality in Public Sector Organizations.

Chernyavskaya *et al.* (2021) discussed how Digital organizational culture can be a separate kind of organizational culture, and highlighted some features which included the organization's ability to process large amounts of digital information quickly and promptly, where data processing is a key element of data management, therefore data processing in specific and data management in general would have an impact on the organization's digital culture and the digitization of the organization, as organizations whoc are characterized by strong digital culture adopt data-driven insights, e.g. access, store, and use data to guide decisions, and build and offer value to concerned stakeholders (Digital Culture Guidebook). However, this has not been tested in the academic literature, therefore, the following hypothesis is proposed.

H1b Data Management impacts positively the Digital Organization Culture in Public Sector Organizations.

5.3.2 Organizational Culture (OC)

Institutionally, Melitski *et al.* (2010) argued that organisational cultures play a role in the approach followed by organizations to adopt or implement technology. Previous research found an association between organizational culture and information technology (Hoffman & Klepper, 2000; Harper & Utley, 2001; Leidner & Kayworth, 2006). The case of introducing new digital technology in an organisation requires organizational changes at different levels, and in these cases, Ke & Wei (2008) considered organizational culture to be significant for the success of projects involving those relevant changes.

Prior studies highlighted the criticality of the fit between a new technological system and organisational culture to enable the organization to gain the potential anticipated benefits from the newly introduced technological system (Martinez-Caro *et al.*, 2020), and thus is considered as one of the key aspects influencing organisational effectiveness (Denison, 1990; Gregory *et al.*, 2009; Zheng *et al.*, 2010).

Fountaine *et al.* (2019) discussed that in order for AI projects to succeed organizations in addition to focusing on cutting-edge technologies and talent, need to give more focus on and attention to organizational culture.

Organizational culture (OC) is considered to have a significant influence on information (Chang & Lin, 2007), and the four cultural traits identified by Denison *et al.* (2004) relate to organizational effectiveness. Petter *et al.* (2013) identified several IS success determinants, one of which was management processes. Denison & Mishra (1995) considered culture as a management process variable and is central to deployment of other business processes, furthermore, culture is essential in developing information systems (Martin, 2002), and implementing relative information systems (Kieso *et al.,* 2020). Nusa (2015) implied that inadequate organizational culture support to information system will result in a system that is inaccurate and not a good quality system. Thus, it is hypothesised that:

H2a Organizational Culture impacts positively the AI system quality in Public Sector Organizations

Martinez-Caro *et al.* (2020) argued that digitisation - adoption and usage of digital technologies – is a transformational process which mandates the building and supporting of a digital culture in the organization that supports this transformation; that is, an organisational culture that is adequate for organisations going through digital transformation. Entities are becoming more aware of the importance of the need to shift their culture in order to be able to achieve their digital strategy and realize its objectives. Llopis *et al.* (2004) highlighted the importance of the relationship between organizational culture and information technology/information systems (IT/IS) and its role in the satisfactory implementation of Technology/Information systems

However, this has not been tested in the academic literature, therefore the following hypothesis is proposed.

H2b Organizational Culture impacts positively the digital organizational culture in Public Sector Organizations

5.3.3 AI System Quality (SQ)

System quality is used to "*refer to the desirable characteristics of the AI system*" (DeLone & McLean, 2003; Halawi *et al.*, 2008), which in this study refers to reliability, user-friendliness, usability and ease of use, ease of understanding, convenient access, and meeting requirements. Those characteristics are important to the organization and internal users of the AI system, because if those systems are not easy to use, understand, or unreliable, organizations and users may feel that the AI system will not deliver the desired output (Sharma & Sharma, 2019), moreover an AI system with unsatisfactorily levels of quality may disturb users' experience as it increases the issues faced during using of AI systems, thus, losing their intention to continue using the system (Zhou, 2013; Sharma & Sharma, 2019).

Mustafa *et al.,* (2020) considered that system quality is used frequently by researchers to measure the success of technology systems, and Petter *et al.*, (2008) considered system quality as a key construct in this conceptual model, as it has an effect on intention to use/use of IS in the public sector organizations, in addition to its effect on the intention to use of the IS system on strategic and operational levels (Bradley *et al.*, 2006; Petter *et al.*, 2008).

According to Mardiana *et al.* (2015) "*Use*" in the DM IS Success Model (Delone & McLean, 2003) is predicted by different predictable variables, one of which is system quality, thus, it is hypothesised that:

H3 AI System Quality impacts positively the actual usage AI system in Public Sector Organizations

5.3.4 Digital Organizational Culture (DOC)

Hess *et al.* (2006) considered that business digitization includes the organization's approach and its capability to explore, adopt, and use new digital technologies therefore, organizations need to be pre-emptive in rebuilding their organizational culture around those approaches and capabilities needed for their business digitization, which requires an adaptive culture to new technologies (Duerr *et al.*, 2018; Bughin & Van Zeebroeck, 2017; Costanza *et al.*, 2016). Therefore this digital related culture or what can be called digital organizational culture (DOC) can lead employees' behaviour in the organization to accept digitization and use digital systems, (Hartmann, 2006).

To successfully develop business digitization, Kane *et al.* (2015) suggested that a digital strategy supported by a digital culture were key drivers to lead digital transformation and separated leaders from others. Therefore, a digital concerned culture is perceived as a prerequisite, in consequence, a new hypothesis explaining the impact of digital organisational culture on the actual usage of AI system is proposed:

H4 Organizational Digital Culture impacts positively the actual usage of the AI system in Public Sector Organizations

5.3.5 Actual Usage

DeLone & McLean (2016) included actual usage in their IS Success Model, and considered it as the degree to which the capabilities of an information system are used. Actual usage can be measured in terms of frequency, nature and duration of use (Aldholay *et al.*, 2018), in this research the frequency and duration of use are used as items for measuring actual usage.

One of the important aspects in technology usage is its impact on other variables, e.g. net benefits, and satisfaction of users or beneficiaries. When using AI related technologies, it is important to assess this impact of such systems/technologies on other variables such as organizational performance (DeLone & McLean, 2016). Several studies have examined the influence of actual usage on performance and reached to different results (Hou, 2012; Son *et al.*, 2012; D'Ambra *et al.*, 2013; Isaac *et al.*, 2017; Makokha & Ochieng, 2014; Ramirez-Correa *et al.*, 2017), nevertheless, researchers concluded that there is a significant relationship between actual usage and each of satisfaction and performance. However, there are contradicting studies, which reached to a conclusion of the insignificance of this relationship (Cho *et al.*, 2015; Wu & Wang, 2006). Consequently, the following hypothesis is proposed:

H5 Actual Usage of the AI system impacts positively the organizational performance in Public Sector Organizations.

5.3.6 Organizational Performance

Abdul Rahman *et al.*, (2019) studied an extended DM IS success Model and proposed net benefits which include organizational performance as a late antecedent to continuation of technology usage intention, which supports what previous researches of Tandi lwoga (2013), and Wu & Wang (2006) concluded that benefits; organizational performance, have an influence on intention to continue usage. Consequently, the following hypothesis is proposed:

H6 Organizational performance impacts positively the intention to AI system usage continuance in Public Sector Organizations.

Figure (5-1) shows the hypothesised model with causal relationships between variables.

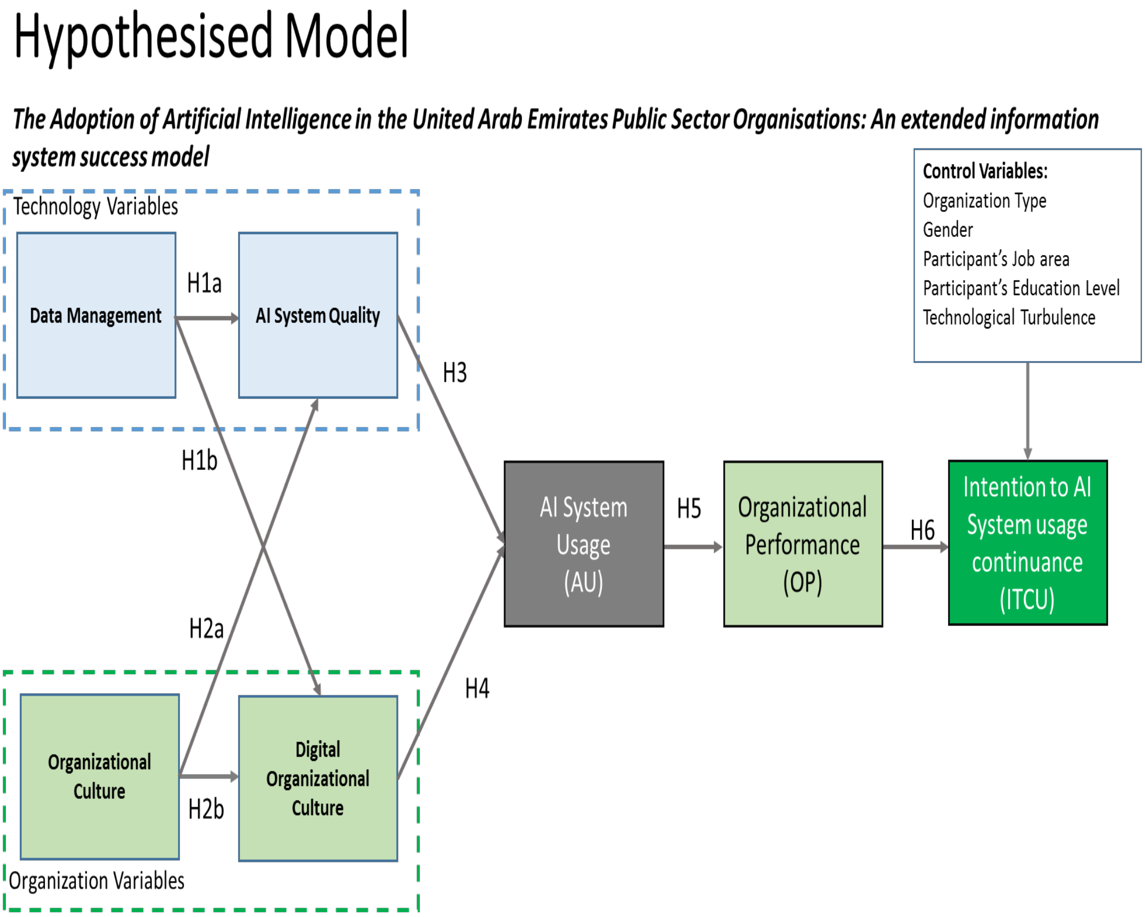

Figure 5-1: Hypothesised Model

5.3.7 Control Variables

Control variables are variables that are controlled in empirical studies (Nielsen & Raswant, 2018), through holding them as constants, and they are controlled to rule out their potential influence on the inferences, and determine the degree of which the proposed constructs behave as per the set hypotheses in the study. In this research, five control variables were used as shown in table (5.1) below:

Table 5-1: Description of control variables

Variable	Category
Organization Type	Federal Government
	Abu Dhabi Government
	Dubai Government
	Sharjah Government
	Ajman Government
	Umm Al Quwain Government
	Ras Al Khaimah Government
	Fujairah Government
Gender	Male
	Female
Job Area	Minister, Managing Director, CEO, Undersecretary , Chief Levels)
	ICT
	Operations (core business of organization)
	Strategy, Business Excellence & Innovation
	Processes & Quality Management
	Customer Service
	Communication & PR
	Social Media
	Legal Affairs
	Internal Audit
	Human Resources Management
	Finance and Accounting
	Procurement Management
	Facilities & Security Management
	Other

Table 5-1: Description of control variables - continued

Variable	Category
Education Level	Doctoral Degree
	Master's Degree
	Bachelor's Degree
	PG Diploma
	Other
Technological Turbulence*	Our industry is characterized by rapidly changing technology
	The rate of technology obsolescence is high in our industry
	It is difficult to forecast the technological changes in the next three years
	Technological changes provide big opportunities in our industry

* source: Khaksar *et al.* (2020).

The technological turbulence was considered as a control variable and defined as "*The rate of technological change in an industry"* (Khasksar *et al.*, 2020).

5.4 OPERATIONALISATION OF VARIABLES

This hypothesized model was built based on literature review, and in order to test it, validated instruments used in previous studies that were relevant to model constructs were identified, then the constructs relevant items were reviewed, adapted, then used in the model as shown in Table (5-2). The following sections briefly discuss the items used in this research to test each respective construct.

Table 5-2: Constructs and Measurement Items

Constructs	Measures	Items	Scales	Sources
Data Management (DM)	Access, Integration, Sharing, Data Cleansing and Meaning	*Using your own opinion and judgement, please state to what extent you agree or disagree with the following:* • **DM1**. The organization has access to very large, unstructured, or fast-moving data for analysis • **DM2**. The organization integrates data from multiple sources into a data warehouse for easy access • **DM3**. The organization integrates external data with internal to facilitate analysis of business environment • **DM4**: The organization has the capacity to share our data across business units and organizational boundaries • **DM5**: The organization is able to prepare and cleanse AI data efficiently and assess data for errors • **DM6**: The organization is able to obtain data at the right level of granularity to produce meaningful insights	7-point Likert Scale: From (1) Strongly Disagree to (7) Strongly Agree	Mikalef and Gupta, 2021; Mikalef *et al.*, 2019)

Table 5-2: Constructs and Measurement Items - continued

Constructs	Measures	Items	Scales	Sources
Organisational Culture (OC)	Involvement; Consistency; Adaptability and Mission	*Using your own opinion and judgement, please state to what extent you agree or disagree with the following:* *In my organisation …* • **OC1:** Decisions are usually made at the level where the best information is available • **OC2:**People work like they are part of a team • **OC3:**Teamwork is used to get work done, rather than hierarchy • **OC4:**There is continuous investment in the skills of employees • **OC5:**There is a clear and consistent set of values that governs the way the organization does business • **OC6:**It is easy to reach consensus, even on difficult issues • **OC7:**People from different parts of the organization share a common perspective • **OC8:**It is easy to coordinate projects across different parts of the organization • **OC9:**The way things are done is very flexible and easy to change • **OC10:**New and improved ways to do work are continually adopted	7-point Likert Scale: From (1) Strongly Disagree to (7) Strongly Agree	(Denison, 1990; Denison *et al.* 2006; Fey and Denison, 2003)

Table 5-2: Constructs and Measurement Items - continued

Constructs	Measures	Items	Scales	Sources
Organizational Culture (Continued)		• **OC11:**Customer input directly influences our decisions • **OC12:** The organization makes certain that the everyone is informed about what is going on across the organization • **OC13:** There is a long-term purpose and direction • **OC14:** There is a clear strategy for the future • **OC15:** There is widespread agreement about goals • **OC16:** Leaders have a long-term viewpoint		
AI System Quality (SQ)	Reliability, User-friendliness, Efficiency, Usability and ease of use	*Using your own opinion and judgement, please state to what extent you agree or disagree with the following:* • **AISQ1:** The AI system is reliable • **AISQ2:** The AI system is user-friendly • **AISQ3:** The AI system is easy to use • **AISQ4:** The use of the AI system is easy to understand • **AISQ5**: The AI system provides convenient access • **AISQ6**: The AI system meets my requirements	7-point Likert Scale: From (1) Strongly Disagree to (7) Strongly Agree	(Delone and Mclean, 2003; Petter *et al.* 2013; Davidson *et al.*, 2020; Bravo *et al.*, 2016, Geebren *et al.*, 2021; Syed *et al.*, 2020; Chang *et al.*, 2018; Alsabawy *et al.*, 2016)

Table 5-2: Constructs and Measurement Items - continued

Constructs	Measures	Items	Scales	Sources
Digital Organizational Culture (DOC)	Collaboration, orientation, change process and staff involvement	*With respect to your organisation, and using your own opinion and judgement, please state to what extent you agree or disagree with the following:* • **DOC1**: The teams collaborate functionally in the initiatives for the innovation and digital transformation • **DOC2**: There is a clear orientation to digital technology changes inside the organization's culture • **DOC3**: The culture of digital innovation and change takes part as a natural process within the organization • **DOC4**: The organization shares with the staff the digital strategy, taking into consideration their suggestions	7-point Likert Scale: From (1) Strongly Disagree to (7) Strongly Agree	(Martínez-Caro *et al.*, 2020)
Actual Usage (AU)	Use of AI	*Using your own opinion and judgement, please state to what extent you agree or disagree with the following:* • **AU1:** The organization uses the AI system for work activities frequently. • **AU2:** The organization uses the AI system a lot. • **AU3:** With what frequency do you personally use AI system in your organization"	7-point Likert Scale: From (1) Strongly Disagree to (7) Strongly Agree Infrequently, Less than Once a month, Once a month, 2-3 times a month, Once a week, Daily	(Kim *et al.*, 2007; Klopping & Mckinney, 2004; Sun *et al.*, (2009)

Table 5-2: Constructs and Measurement Items - continued

Constructs	Measures	Items	Scales	Sources
Organisational Performance (OP)	Organizational performance due to adoption of Artificial Intelligence System	*Using your own opinion and judgement, please state to what extent you agree or disagree with the following:* • **OP1:** Artificial Intelligence can provide us with more accurate data. • **OP2:** Artificial Intelligence can enhance Employee satisfaction. • **OP3:** Artificial Intelligence can enhance Quality of products and/or services. • **OP4**: I believe that Artificial Intelligence can enhance the organization's financial performance. • **OP5**: Artificial Intelligence can enhance the organization's operational performance. • **OP6:** Artificial Intelligence can increase customer satisfaction. • **OP7:** Artificial Intelligence resulted in improving business processes.	7-point Likert Scale: From (1) Strongly Disagree to (7) Strongly Agree	(Yadegaridehkordi *et al.*, 2020; Mikalef *et al.*, 2019; Wamba *et al.*, 2019)
Intention to AI System Usage Continuance	Intention to continue using the AI system	*Using your own opinion and judgement, please state to what extent you agree or disagree with the following:* • **IUC1:** Our organization intends to continue the use of AI system in the future. • **IUC2:** Our organization intends to increase the use of AI systems in the future. • **IUC3:** Our organization's intentions are to continue using the AI system than use any alternative means.	7-point Likert Scale: From (1) Strongly Disagree to (7) Strongly Agree	(Abdul Rahman et. Al., 2019; Hong *et al.*, 2006)

5.4.1 Measuring Data Management

Items measuring Data Management were adapted from Mikalef and Gupta, (2021); and Mikalef *et al.*, (2019), which covers different aspects including; data access, data internal and external integration and sharing, data cleansing and finally ability to obtain meaningful insights from data. Data Management was measured by using six statements.

5.4.2 Measuring Organizational Culture

The items used for measuring organisational culture were adapted from the model originally developed by Dan Denison and other researches: (Denison, 1990; Denison *et al.* 2006; Fey and Denison, 2003). This model included four dimensions: adaptability which covered team work, involvement in decisions, and investments in employees' skills. Consistency: involved ease of reaching consensus among employees, building common perspectives, shared values, and coordination. This dimension is involvement, which measured areas such as flexibility or agility, innovation, listening to voice of customers, and open communication, and lastly, mission which measured long term direction, leaders' vision, agreement on direction and availability of strategy.

The framework is a perception measure of the degree the adoption of the items of each dimension is present in the public sector organization. Organisational culture in this study was measured by using sixteen statements adapted from Denison

5.4.3 Measuring AI System Quality

The Delone and Mclean, 2003 and Petter *et al.*, 2013 variable: System Quality was used, and the items measuring the AI system Quality in this study were adapted from studies of Delone and Mclean, 2008; Petter *et al.* 2013; Davidson *et al.*, 2020; Bravo *et al.*, 2016 ; Alsabawy *et al.*, 2016; Geebren *et al.*, 2021; Mustafa *et al.*, 2020; Chang *et al.*, 2018, they covered aspects of reliability, user-friendliness, efficiency, usability and system's ease of use. System quality comprised of six statements.

5.4.4 Measuring Digital Organizational Culture

Measures assessing Digital Organizational Culture were adapted from (Martínez-Caro *et al.*, 2020). DOC was measured according to four areas; collaboration, orientation, process of change, and staff involvement; it comprised of a total of four statements; one for each area.

5.4.5 Measuring actual usage of AI system

There are several measures proposed by Delone and McLean (2003) to measure use but in this study the measures used for assessing actual usage of AI system were adapted from (Sun *et al.*, 2009; Klopping & Mckinney, 2004). Actual usage was measured in terms of frequency of use, and degree of use (a lot).

5.4.6 Measuring Organizational Performance

It has been reported in existing studies that there is a positive connection between technology usage and performance of organizations (Garrison *et al.*, 2015). IS systems can improve the financial and non-financial performance of the organization in areas of data accuracy (as an output), satisfaction of employees and customers, quality of products and services, financial and operational performances, in addition to organizational processes (Yadegaridehkordi *et al.*, 2020; Mikalef *et al.*, 2019; Wamba *et al.*, 2019).

5.4.7 Measuring Intention to AI system usage continuance

Measures assessing intention to continue using the AI system were adapted from (Abdul Rahman *et al.*, 2019; Hong *et al.*, 2006). Intention to continue usage was measured in terms of intention to continue using the AI system in the future, the intention to increase the usage, or the intention to continue with the organization preference to use the AI system.

5.5 CONCLUSION

This chapter presented the constructs identified in the literature review and theoretical framework, then discussed the proposed conceptual model used in this study. Eight hypothesis were discussed and relationships in the model were identified. The chapter also illustrated the operationalization of the variables.

The next chapter will discuss the data collection and analysis processes followed in this study in addition to testing the structural model.

CHAPTER SIX: DATA COLLECTION AND QUANTITATIVE ANALYSIS

6.1 INTRODUCTION

This chapter covers two main processes used in this study: the data collection, and quantitative analysis, followed by presenting the results. The data collection method was through a survey approach, in which validated instruments and reliable scales adopted in previous studies were used to design the questionnaire. The Structured Equation Modelling (SEM) was applied to conduct quantitative analysis. The tools used were:

- Statistical Package for the Social Sciences (SPSS) was used for the descriptive statistics to describe the constructs, sample and characteristics of the respondents.
- Analysis of Moment Structures (AMOS) software was used to visualise the SEM model, and assess conceptual model's constructs relationship fit.

Outputs of this chapter are of three parts: Confirmatory Factor Analysis (CFA); the structural model; and results of examination of hypotheses in the conceptual model.

6.2 QUESTIONNAIRE DESIGN

The next step in this research is to design the questionnaire, which is the quantitative data collection method. As discussed in chapter 3, a survey approach was selected and applied to collect data related to public sector organizations' intention to continue usage of AI technologies. This was conducted through a cross-sectional study across federal and local levels of the government in the United Arab Emirates. This section illustrates the rationale and steps followed in questionnaire design in this study.

The survey approach has several strengths as follows: Through survey design perceptions or attitudes of a population are quantified and numeric research description can be presented by studying a representative sample of that population (Fowler, 2009). A Questionnaire includes a set of questions and is used to collect data through targeting a population and asking them to respond to the questions, and the respondents' replies or answers are collected, codified, if needed, then analysed by software (Saunders *et al.,* 2019). Additionally, Tashakkori & Teddlie, (2010) noted that questionnaires are considered relatively inexpensive, can protect anonymity of respondents, and the data collected is easy to analyze, moreover in case of validated and well-constructed questionnaires, the validity of the used measurements and their reliability are moderately high.

To maximise benefits of using questionnaire design, DeVaus (2014) stressed the importance of giving careful consideration to design of questionnaire including clear layout and purpose, the planning, pilot testing, and administration of the questionnaire, as it has an effect on the survey response rate, in addition to the validity of the collected data and its reliability. The data collection for this study was based on the perceptions, opinions and judgements of the respondents, which was collected through the online questionnaire used.

McDaniel & Gates (2013) states that there is a logical sequence of steps that should be followed when designing a questionnaire. While these steps may alter slightly among researchers, they commonly follow the same general path. Consequently, eight main steps were followed in designing and administrating the questionnaire as shown in Figure (6-1).

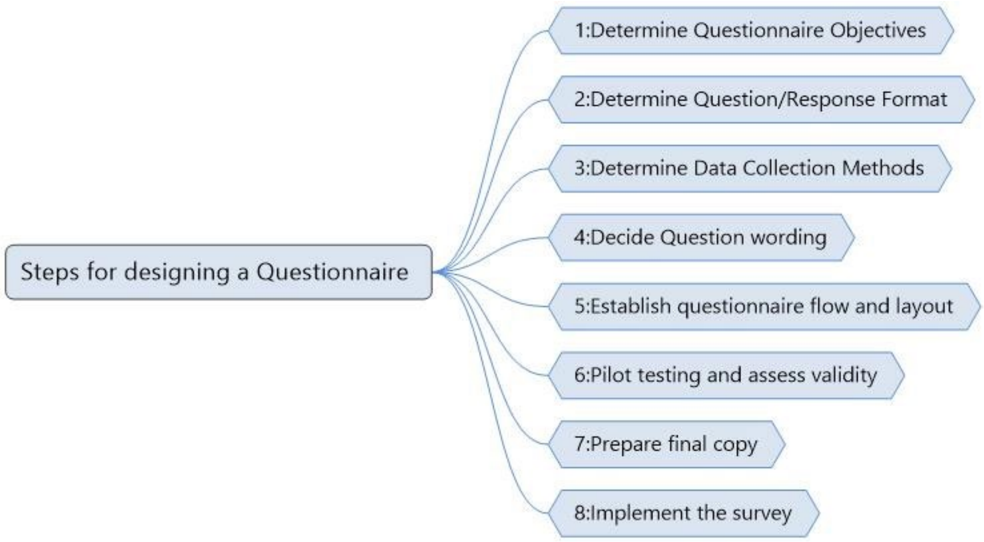

Figure 6- 1: Steps of Designing Questionnaire

The following sections will details how the online questionnaire was designed.

1- Determine questionnaire's objectives:

This questionnaire is designed in order to meet one of the three research objectives set, through testing the research conceptual model, and examining the relationships between variables that affect the intention of public sector organizations to continue to use AI technologies.

2- Determine question/response format:

When determining questions format, the questions format and kind of scales need to be taken into consideration. In this study, the new conceptual framework derived from the literature review was the base for phrasing questions used in the survey. As for the kinds of scales, nominal scales were used for categorising respondents based on their demographic characteristics and organisational profiles, whereas the ordinal scales were used to collect respondents' perceptions, opinions, and judgements in relation to the questionnaire items, in addition to testing the relationships between the research model's constructs. The questionnaire consists of **55** closed questions and **1** open-ended, and includes rating on a seven-point Likert scale, as well as different sorts of questions provided by the web based questionnaire design software (onlinesurveys.ac.uk). In this study, *Appendix* "A" includes the entire survey used.

Table 6-1 lists the questionnaire's objectives aligned to research constructs, and the eight hypotheses, in addition to scales used and proposed question numbers. As discussed in Chapter 5, prior relevant research and validated item were adapted and used to operationalise the proposed constructs.

Table 6- 1: Objectives, Hypotheses, Variables, Hypothesised Relationships, Scales, and Questions numbers

Objectives	Constructs	Hypothesis	Hypotheses Relationships	Scales	Questions Numbers
Identify Participant's demographic characteristics, profiles and AI adoption status in addition to AI technologies adopted		---------------------------------	-------------------	Nominal	1-10
Investigate the influence of Data Management (DM) on System Quality (SQ) and Digital Organizational Culture (DOC)	Data Management **(DM)**	**H1a:** There is a positive and significant relationship between Data Management (DM) and System Quality (SQ) in Public Sector Organizations. **H1b:** There is a positive and significant relationship between Data Management (DM) and System Quality (SQ) in Public Sector Organizations.	**DM → SQ** **DM → DOC**	7 points Likert Scale	37-42
Investigate the influence of Organizational Culture (OC) on System Quality (SQ) and Digital Organizational Culture (DOC)	Organizational Culture **(OC)**	**H2a:** There is a positive and significant relationship between Organizational Culture (OC) and System Quality (SQ) in Public Sector Organizations. **H2b:** There is a positive and significant relationship between Organizational Culture (OC) and Digital Organizational Culture (DOC) in Public Sector Organizations.	**OC → SQ** **OC → DOC**	7 points Likert Scale	11-26

Table 6- 1: Objectives, Hypotheses, Variables, Hypothesised Relationships, Scales, and Questions numbers - continued

Objectives	Constructs	Hypothesis	Hypotheses Relationships	Scales	Questions Numbers
Investigate the influence of System Quality (SQ) on Actual Usage (AU)	System Quality **(SQ)**	**H3:** There is a positive and significant relationship between System Quality (SQ) and Actual Usage (AU) in Public Sector Organizations.	**SQ → AU**	7 points Likert Scale	31-36
Investigate the influence of Digital Organizational Culture (DOC) on Actual Usage (AU)	Digital Organizational Culture **(DOC)**	**H4:** There is a positive and significant relationship between Digital Organizational Culture (DOC) and Actual Usage (AU) in Public Sector Organizations.	**DOC → AU**	7 points Likert Scale	27-30
Investigate the influence of Actual Usage on Organizational Performance (OP)	Actual Usage **(AU)**	**H5:** There is a positive and significant relationship between Actual Usage (AU) and Organizational Performance (OP) in Public Sector Organizations.	**AU → OP**	7 points Likert Scale	43-45
Investigate the influence of Organizational Performance (OP) on Intention to Continue Usage (ITCU)	Organizational Performance **(OP)**	**H6:** There is a positive and significant relationship between Organizational Performance (OP) and Intention to Continue Usage (ITCU) in Public Sector Organizations.	**OP → ITCU**	7 points Likert Scale	46-52

Table 6- 1: Objectives, Hypotheses, Variables, Hypothesised Relationships, Scales, and Questions numbers - continued

Objectives	**Constructs**	**Hypothesis**	**Hypotheses Relationships**	**Scales**	**Questions Numbers**
Examining the organization's Intention to Continue Usage (ITCU) of the AI system(s)	Intention to Continue Usage **(ITCU)**	----------------------------------	------------------ --	7 points Likert Scale	53-55
Collect more feedback from participants through an open question		----------------------------------	------------------ --	Nominal	56

In order to facilitate filling the questionnaire on the participants, the questionnaire begins with enquiring about the participant's willingness to participate. If "YES", then he can continue filling the questionnaire, but If "NO", the questionnaire is ended automatically and the respondent is taken to a page with a thank you message.

To simplify the filling process, the questions were categorised into six sets listed below, and used only six screen pages. All participants could save their responses, and they were given the freedom to navigate the survey screen pages survey pages and make changes to their replies.

- *Part One:* Respondents information and organizational profiling
- *Part Two:* AI Adoption Status in the organization
- *Part Three:* System Quality and data management
- *Part Four:* Organisational Culture and digital organizational culture
- *Part Five:* Actual Usage, Organizational Performance and Intention to continue Usage
- *Part Six:* Participants' comments (Open question)

Part one of the questionnaire consisted of ten questions covering organisational profile and the respondent's demographic characteristics in addition to professional details. This included questions on government type (federal vs. local), technological turbulence in their industry, participant's gender, job area, and managerial level, in addition to type of AI technology used in case of using any AI technology.

Part two of the questionnaire involved questions on the organization's current AI adoption status in the organization. Question 9 was used to enquire about AI adoption status in the organization, if the answer was YES, then an additional question is opened about what AI technologies are currently being used. If the answer was NO, then Question 10 was used to clarify the reasons for not adopting AI technologies yet, and the questionnaire goes to last page with a thank you message.
Parts from three to six of the questionnaire involved 44 closed questions adapted from the previously validated items in prior studies related to the constructs of the proposed model.

Part three included organizational dimension questions. Questions 11 to 26 covered the organizational culture questions through measuring its traits; 11-14 measured involvement, 15-18 consistency, 19-22 adaptability, and 23-26 the organisation's mission. The digital organizational culture was measured from participants' perception by questions 27 – 30.

Part four measured the technology dimension. Questions 31 – 36 measured the participant's perception regarding AI System Quality, and questions 37 – 42 focused on data management.

Part five covered the participants' perceptions on "Actual Usage" through questions 43 – 45, then questions 46-52 focusing on organizational performance, and finally 53-55 measured the intentions to AI technologies usage continuance.

In the final part, an open-ended question was used to ask participants to comment or give feedback based on their experience with AI technologies usage in public sector organizations. Lastly, participants were offered the opportunity to provide their email address, if they wished to receive a softcopy summary of research findings. Following this, the pages go to the last page to thank the respondents for their time and participation.

3- Determine data collection methods:

It is essential to determine sort of technique that is going to be used to collect the primary data from target participants using a questionnaire, such as internet and intranet-mediated questionnaires, telephone, personal meeting face- to-face, and/or a combination of them (Saunders *et al.* 2019). The selected techniques will enable reaching more respondents and encouraging them to participate, nevertheless, a higher response rate depends on several other factors one of which is the clear wording and lay out of the survey when designing the questionnaire.

The potential participants were contacted through approaching their organizations via email or telephone enquiring about contact person, or through asking the organization via email to forward the questionnaire to employees in different functions and locations through intranet and e-mail. Accordingly, the method chosen to collect primary data was through self-completed internet questionnaire.

4- Decide Questions wording:

This study followed a deductive approach were two tested models, DM IS Success Model and T.O.E. framework, were integrated to build the conceptual model presented in Chapter 5, which was examined in this study. This new hybrid model included seven constructs identified through the conducted literature review, and for each one of those constructs, previous studies were reviewed and relevant items were identified. Those identified items were used as questions in the online survey to examine measure(s) relevant to that construct, and all of those questions were selected from previously tested studies published in peer reviewed journals as listed in Table (5-2), for example items in the Data Management construct were used to measure: Access to data, data integration, data sharing, data cleansing, and meaningful insights. Figure (6-2) shows the main steps followed to prepare questionnaire items.

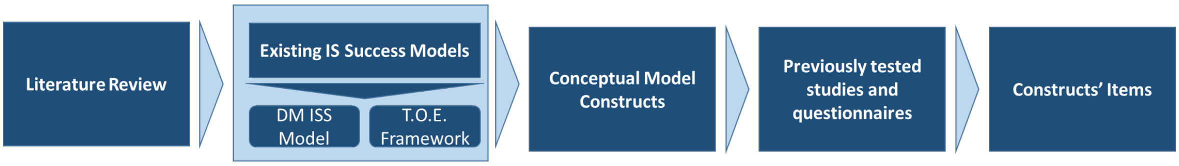

Figure 6- 2: Steps to prepare Questionnaire items

The phrasing of each question through appropriate wording is imperative to ensure that the responses received are valid and accurately measure what is intended from the question (Saunders *et al.*, 2019; Cooper & Schindler, 2013). Wordings from previous validated studies were used to ensure adequacy of responses and minimise any participant's biases and measurement errors levels, in addition simple wording was considered for all questions in the study to avoid ambiguity in understanding the questions.

5- Establish questionnaire flow and layout:

Survey layout and sequence of questions were taken into consideration, eligibility questions were used to screen out unqualified respondents. Interest of respondents was built gradually from warm up questions followed by questions inthe middle half of the questionnaire requiring more concentration. In order to encourage the respondent to keep filling the questionnaire till the end, the open-ended question was the last question asked.

6- Pilot testing:

The electronic questionnaire was reviewed, then a pilot study was run in order to get feedback to improve the questionnaire and eliminate potential issues before officially administering it to the targeted organizations. The pilot survey was run online via emails sent to 30 participants to give their feedback time needed to fill the survey, and on validity and clarity of questions. The pilot survey were accessed on this link:

https://northumbria.onlinesurveys.ac.uk/ai-adoption-in-public-sector-03022022-v1

The sample used in the pilot testing comprised of: 22 potential respondents; four IT professionals; and four ICT knowledgeable researchers. Two weeks, from 1st to 20th February 2022, were given for the pilot study. In total, the response rate was 73.33%, as twenty two questionnaires were received back, and the respondents' feedback was analysed, and then used to improve the survey and its validity, clarity and language of questions, expected duration and where the respondents started to lose interest. The participants in the pilot study were excluded from the final data collection.

The internal consistency test "Cronbach's alpha" was used to test the reliability of the measures adopted in the questionnaire, that is to measure reliability of each variable in addition to identify whether these are measuring the criterion in question. In general, there is a scale range to accept the values of alpha and consider it reliable; alpha is above 0.7 (Pallant, 2010) and less than 0.95 (Hair *et al.*, 2019), while Nunnally, (1978) noted that an alpha score of (0.6 - 0.7) can be also considered acceptable.

In this study, the reliability for each variable in the questionnaire was measured through Cronbach's alpha coefficient. Table 6-2 presents the constructs, number of items and their respective Cronbach's alpha coefficients:

Table 6- 2: Reliability and Internal Consistency

Constructs	Items	Cronbach's Alpha
Data Management (DM)	6	0.860
Organizational Culture: Involvement (INV)	7	0.844
Organizational Culture: Consistency (CNS)	6	0.660
Organizational Culture: Adaptability (ADP)	7	0.463
Organizational Culture: Mission (MIS)	7	0.646
All items of Organizational Culture (OC)	*27*	*0.884*
AI System Quality (SQ)	6	0.750
Digital Organizational Culture (DOC)	4	0.641
Actual Usage (AU)	2	0.897
Organizational Performance (OP)	7	0.643
Intention to Continue Usage (ITCU)	3	0.890

Most of the variable's reliability score exceeded (0.7), as they were ranging from 0.750 to 0.897, except variables CNS, MIS, DOC and OP which were above 0.6 but less than 0.7, ranging from 0.643 to 0.660, whereas, ADP variable's reliability score was less than (0.6). This required a review of the questions used for all organizational culture items, while keeping the reliable items (ones with high alphas).

7- Prepare final copy:

In order to prepare the final copy, inputs from the pilot survey participants were used to revise the survey and its questions. As previously discussed, the questionnaire had been designed taking into consideration several factors such as appropriate phrasing of questions, and the flow of questions, notably it was developed for the purpose of answering the research question, examining the hypotheses, and based on prior quantitative studies, in addition to the feedback from pilot test respondents.

Then the researcher prepared an invitation package comprising of covering letter, an information sheet, and a consent form to be distributed to invite participants to fill in the final survey, which included: an introductory page with information about the purpose of the survey, its content, filling guidelines, and maintaining anonymity and confidentiality. Additionally, participants were offered the option to request a summary of the survey findings.

8- Spreading the survey:

Based on all the previous steps and feedback, the online survey engine "Onlinesurveys.ac.uk", which was provided by Northumbria University, was used to design and construct the survey using its built-in tools, and then posted on the following website: **https://northumbria.onlinesurveys.ac.uk/ai-adoption-uae**

Participants in public sector organizations in the UAE received emails with invitation package which included documents prepared in the above step 7 "*Prepare final copy*" and a link to the questionnaire. *Appendix* A illustrates the invitation package in addition to a copy of the entire survey.

The electronic questionnaires were distributed over a period of seven and half months; from 22nd February to 30th September 2022, where potential participants in public sector organizations were contacted via e-mails, and professional networks; LinkedIn. Organizations and participants were contacted for follow-up through e-mail correspondence and telephone contacts. Moreover, the researcher followed-up with organizations approximately 14 days after the initial contact, where reminders were e-mailed to participants.

6.3 SAMPLING TECHNIQUES

As discussed in chapter 4, sampling techniques are used to optimise data collection from a representative sample of a population rather than from all elements of the population (Saunders *et al.,* 2020). Moreover, there is a big challenge and access restrictions to reach to the entire population of public sector organizations and collect data from all targeted entities.

This research is targeting a population of decision makers, managers, IT professionals and employees who are using AI technologies in public sector organizations in the United Arab Emirates. Non-probability sampling techniques were used due to the lack of access to reliable and clear data related to AI adoption in the public sector organizations in the United Arab Emirates, therefore, the sample was selected in a non-random manner.

The sampling techniques used in this study are self-selection sampling and snowball sampling, which were discussed in previous section 4.6.2. Thus, this study used an online questionnaire targeting potential decision makers, managers, ICT professionals and potential users in public sector organizations in the United Arab Emirates, who were sent an invitation asking them to participate in the survey through filling in the online questionnaire, and where applicable, identify other fellow colleagues or participants in other public sector organizations in the United Arab Emirates, who are interested in this study.

6.3.1 Sample Size

The decision for the size of the sample needed for this study was affected by the requirements for the selected statistical analysis method; Structural Equation Modelling (SEM), in addition to other factors such as resources availability, degree of data accuracy and reliability, available timeframe for the study, and segmentation of the respondents (DeVaus, 2002; Saunders *et al.*, 2019).

Hair *et al.,* (2019) illustrated that Structural Equation Modelling (SEM), which is used in this study, like most of other statistical analysis techniques require a convenient sample size to run the analysis in order to obtain reliable estimates, and it is recommended by different authors to obtain a sample size greater than 200 in order to for the SEM to provide analysis results including goodness-of fit and parameter estimates with acceptable confidence levels (Hair *et al.*, 2019; Boomsma & Byrne, 2010; Kline, 2005, Hoogland, 2001; Gerbing & Anderson, 1993; Harris & Schaubroeck, 1990).

The official UAE government website (https://u.ae/en/about-the-uae/the-uae-government) refers to list of public sector organizations on federal and local levels. Organizations were approached through official emails or contact numbers and eventually a total of 614 emails were sent in order to receive responds from a representative sample and maximise the response rate.

6.4 DATA COLLECTION AND ANALYSIS

The purpose of this chapter is to analyse the data collected using the adopted statistical methods and present the findings. To meet research objective number 3 of this study, statistical tools SPSS (version 27.0) was used to conduct the analysis on collected preliminary data, and AMOS (version 28) application was utilized for the measurement model analysis, and test the proposed hypothesised model in the Structural Equation Modelling (SEM).

The following sections cover the response rate achieved, followed the analysis of respondents' profiles both demographic and professional ones, summary of the demographic characteristics and profiles, and then descriptive statistics.

6.4.1 Response Rate

Out of the 614 questionnaires sent, the researcher received 260 completed questionnaires, with a response rate of 42.3%. However, 25 responses replied back with a "NO" for adopting AI technologies, and 12 responses were discarded because they had given fixed Likert scale answers to all items. Figure (6-3) illustrates that 223 questionnaires were used for further data analysis, with a response rate of 36.3%.

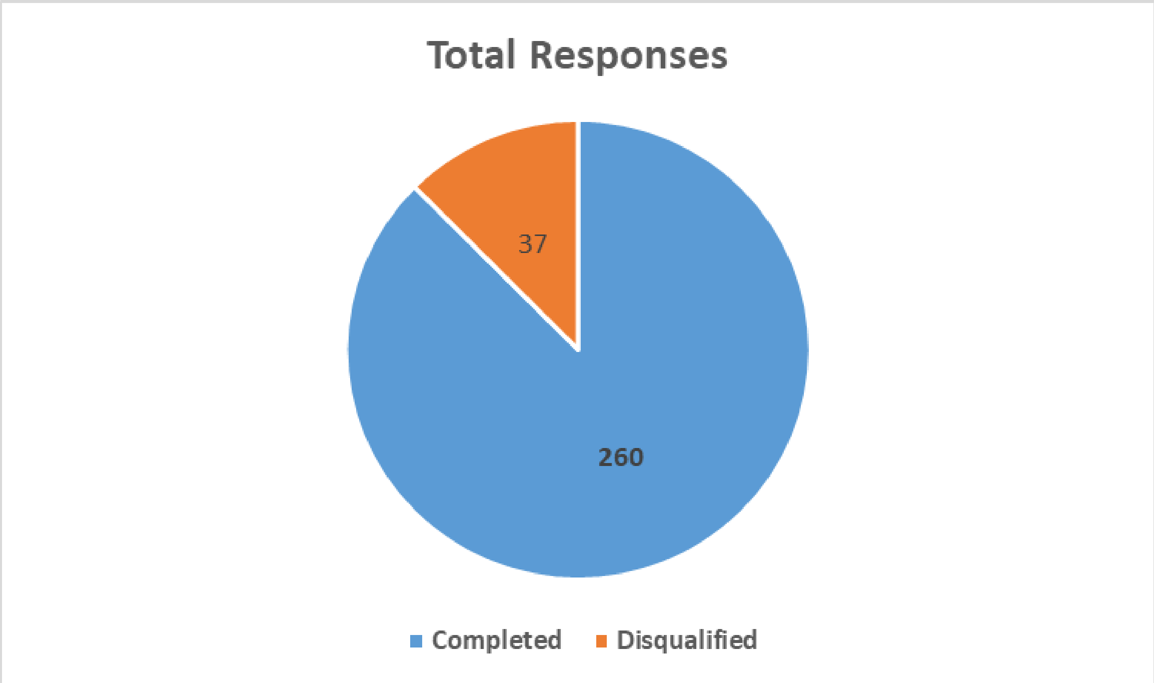

Figure 6- 3: Total Responses of the Questionnaire

6.4.2 Respondents ' Characteristics and Profiles

This section describes the demographic and professional profiles of participants and the organizations they work in, which will help in clarifying the context of research findings. The 223 respondents represent a variety of public sector organizations on different government types; federal vs. local, in addition to different managerial levels with different education backgrounds and different functions, and in different government types. The survey questionnaire targeted decision makers, managers, ICT professionals, employee users working in public sector organizations in the United Arab Emirates who are using AI technologies in their respective organizations. The following survey questions were used to create those profiles.

Gender:

The male respondents formed the majority of the respondents with (61%). See Figure 6-4.

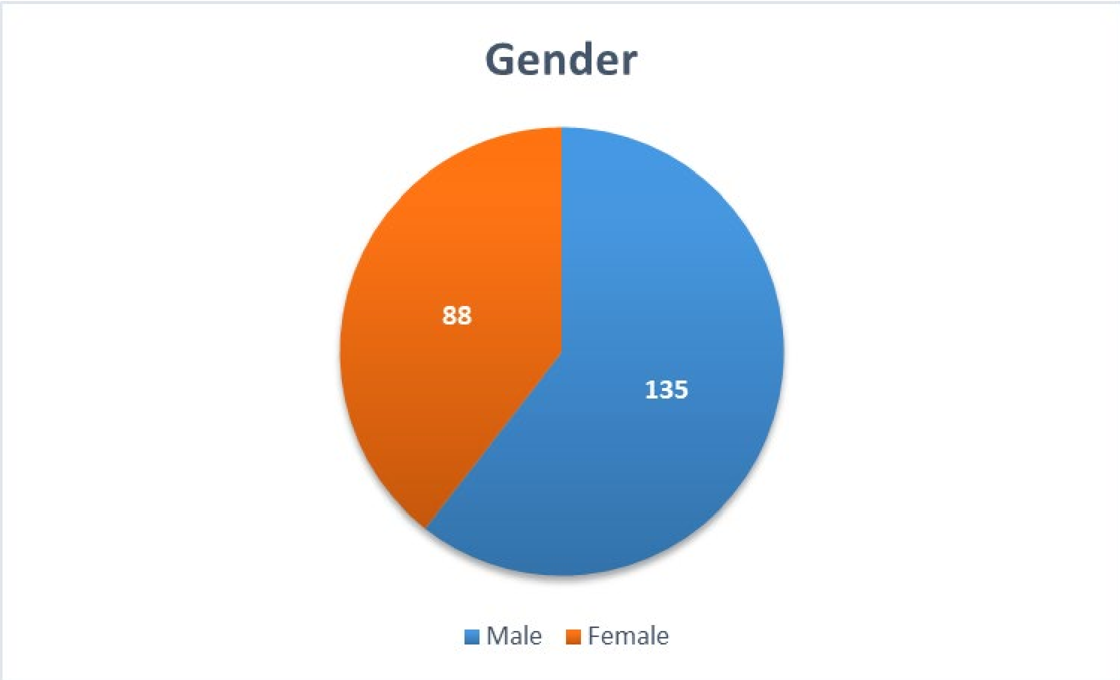

Figure 6- 4: Gender

Government Type:

Each participant was asked to indicate the type of government they work in. Respondents in Abu Dhabi Government formed (37%) of the responses, followed by respondents from the UAE federal government (30%), then respondents from Dubai Government (26%). The results are presented in Figure 6-5.

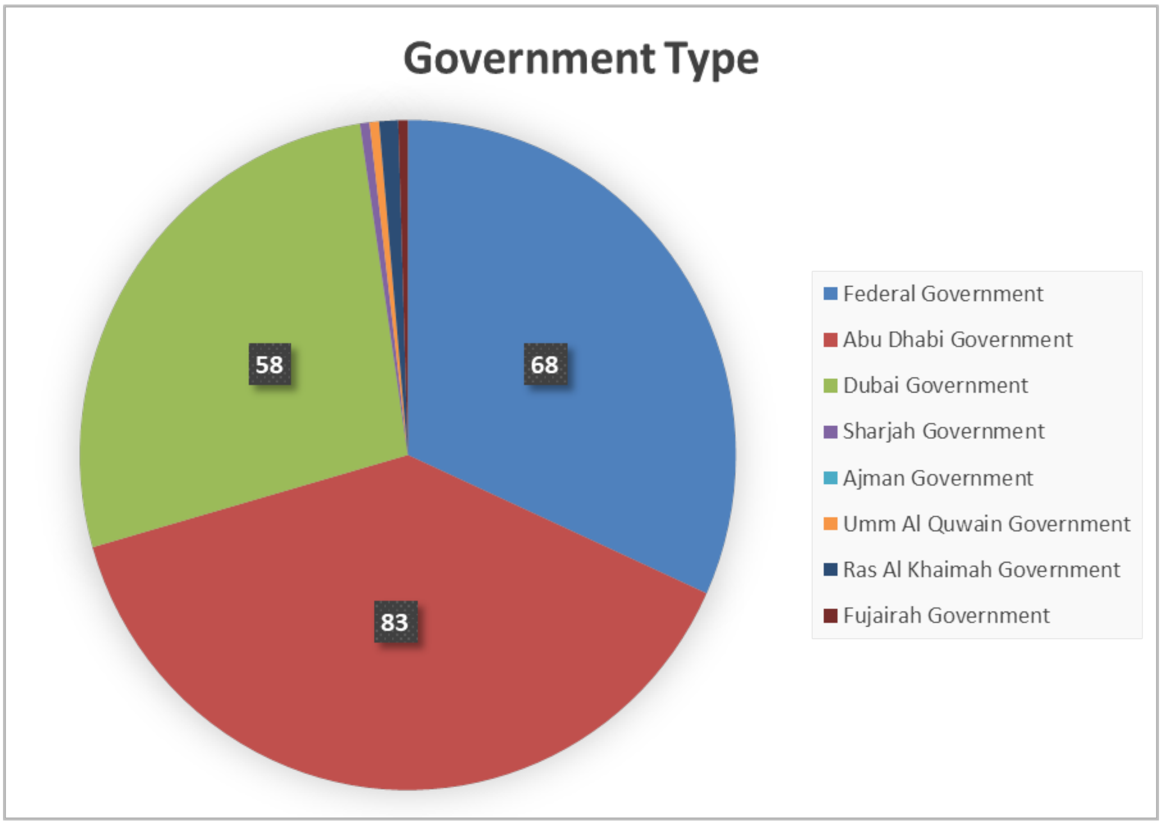

Figure 6-5: Government Type

Job Area:

The largest percentage of the respondents were from Strategy, Business Excellence and Innovation (22%), then Operations (17%), and ICT Professionals (12%). Figure 6-6 shows the job area of respondents.

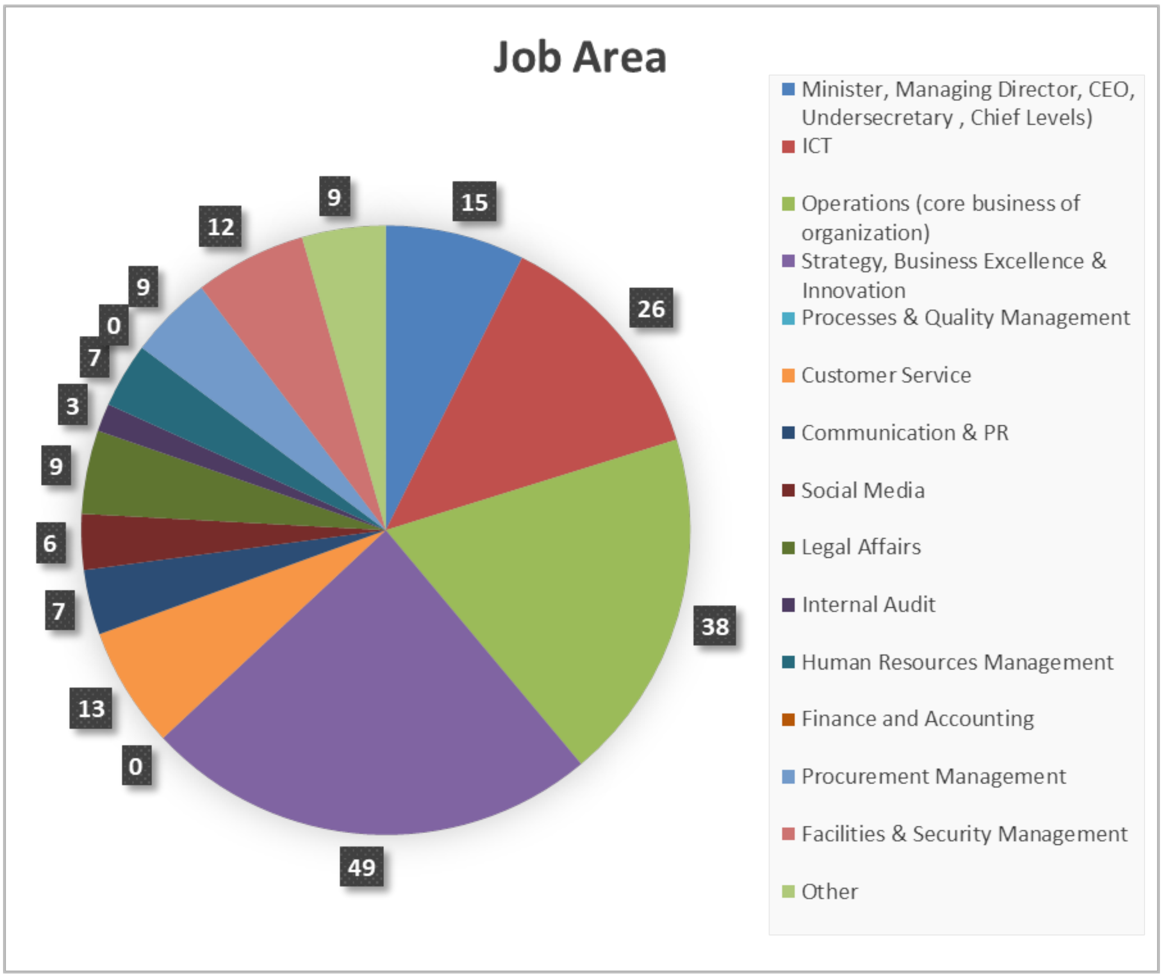

Figure 6- 6: Job Area

Education Level:

All of the respondents finished their school education. The largest percentage of the respondents hold Bachelor's degree with a percentage of (57%) then the Master's Degree (34%). Figure 6-7 shows education level of respondents.

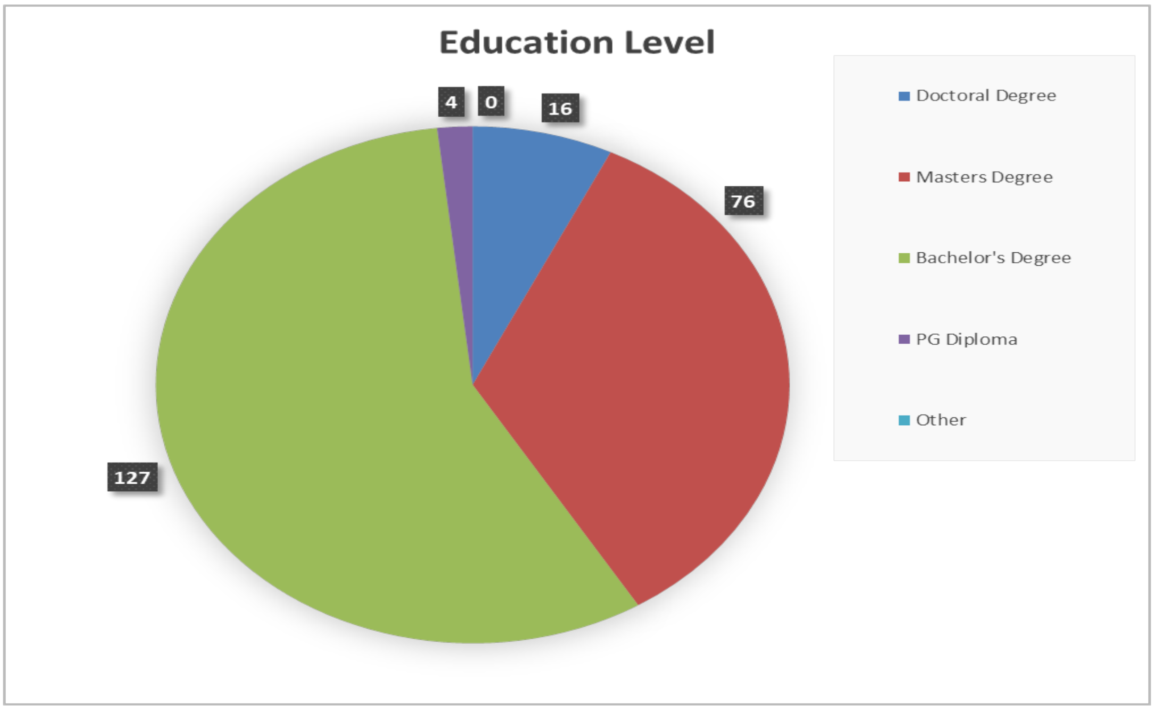

Figure 6-7 Education Level of respondents

Technological Turbulence:

Participants were asked to select the best description the technological turbulence in their industry. (37%) of the respondents considered that "*Technological changes provide big opportunities in our industry*". The results are presented in Table 6-8.

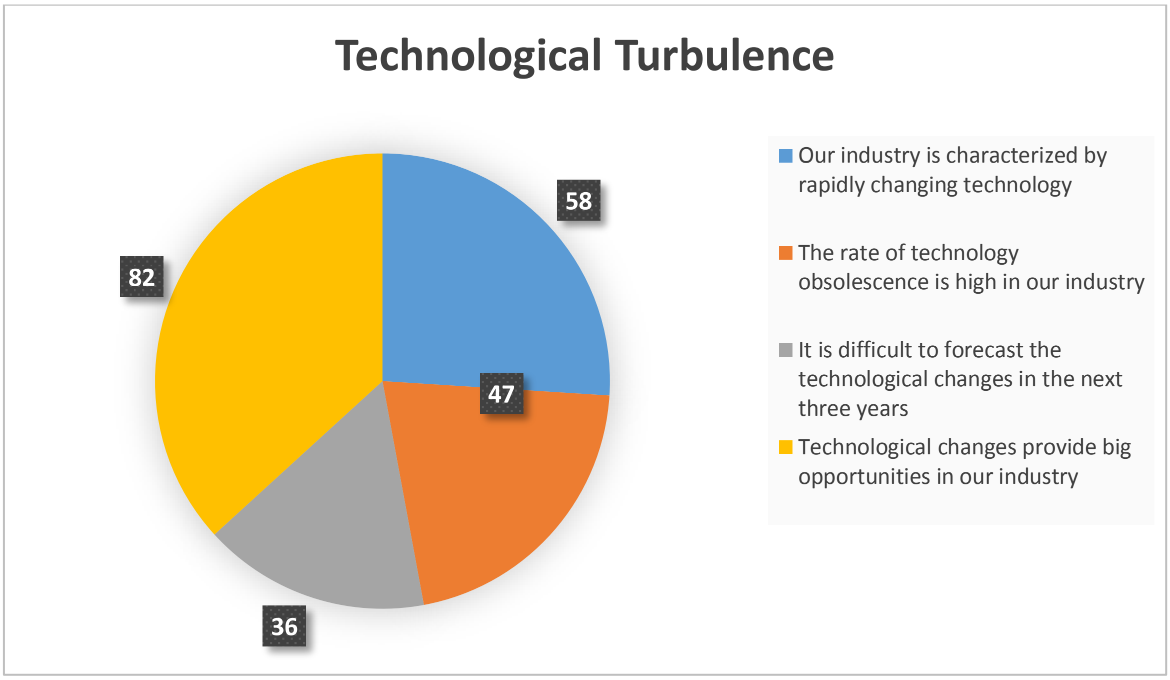

Figure 6-8 Technological Turbulence

Frequency of AI systems usage

In this survey, another level of usage verification was added to ensure respondents filling the questionnaire are using AI related technologies system. The results are presented in Figure 6-9, with 32% using the AI system 2-3 times a week, 29% weekly, and 23% on daily basis.

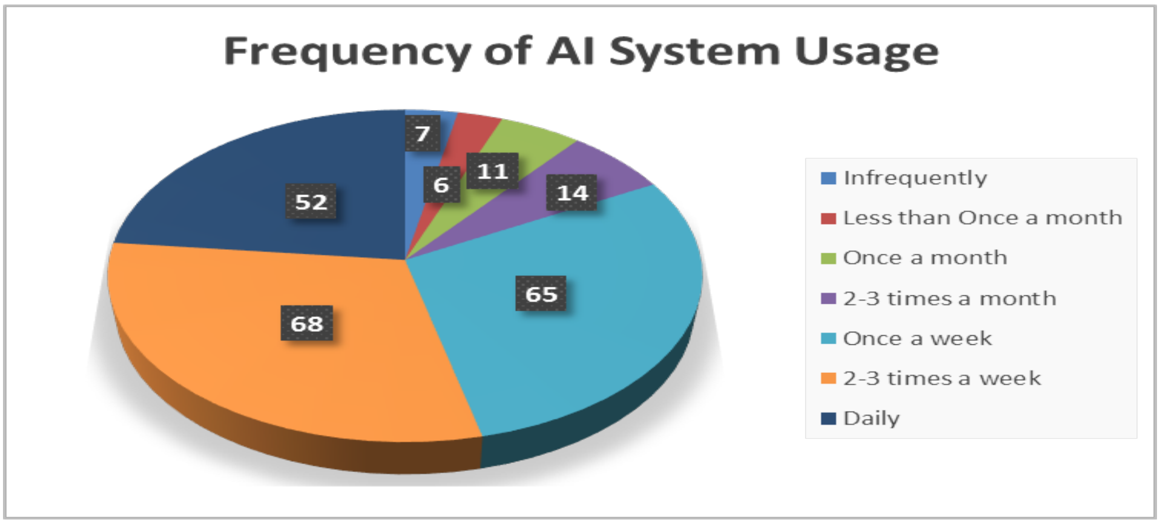

Figure 6-9 Frequency of AI system usage

AI technologies used in public sector organizations

This purpose of this question is to identify AI technologies used in the public sector organizations, therefore participants were asked to select the AI technologies that are used in their respective organisations. The study identified through the literature review a list of eighteen AI technologies, which was presented in the survey for the participants to choose the applicable number of technologies. The analysis revealed that the technologies are used in public sector organizations in different percentages, for example "Machine Learning Platforms" and "Virtual Agents" are the most frequently used technologies with (30%), then the Cyber Defence with (23%), whereas is the least used technology was manufacturing robots with (4%). Table 6-3 illustrates the AI related technologies used in public sector organizations.

Table 6- 3: AI related Technologies Used in Public Sector Organizations

	AI Technologies	Frequency	%
AI Technology(ies) Adopted	Natural Language Generation	**32**	**14%**
	Speech Recognition	**38**	**17%**
	Machine Learning Platforms	**67**	**30%**
	Virtual Agents (e.g. Chat bots)	**66**	**30%**
	Automated Decision Management	**45**	**20%**
	AI Optimized Hardware	**30**	**13%**
	Deep Learning Platforms	**49**	**22%**
	Robotic Process Automation	**46**	**21%**
	Text Analytics and Natural Language Processing (NLP)	**29**	**13%**
	Bio-metrics	**30**	**13%**
	Cyber Defense	**52**	**23%**
	Content Creation	**16**	**7%**
	Emotion Recognition	**17**	**8%**
	Image Recognition	**34**	**15%**
	Marketing Automation	**20**	**9%**
	Manufacturing robots	**10**	**4%**
	Self-driving cars	**12**	**5%**
	Smart assistants	**32**	**14%**
	Other	**5**	**2%**

6.4.3 Summary of respondents' profiles

Based on the analysis of participants' answers in part 1 of the survey, the demographic characteristics and profiles can be presented as follows:

6.4.2.1 Public Sector Organizations from different levels (federal vs. local governments).

6.4.2.2 A variety of positions in Public Sector Organizations

6.4.2.3 Different types of functions.

6.4.2.4 Mixed gender (male and female)

6.4.2.5 Different job levels.

6.4.2.6 Varied educational backgrounds

6.4.2.7 Use different AI related technologies.

In summary, all respondents confirmed that they are working in a public sector organization and using AI related technologies in their respective organizations, therefore their responses can be used to examine the intention to continue using AI technologies in public sector organization. Table 6-4 summarises the respondents' demographic characteristics and profiles.

Table 6- 4: Demographic Characteristics and Profiles of Survey Respondents (n=223)

Variable	Category	Frequency	%
Organization Type	Federal Government	**68**	**30%**
	Abu Dhabi Government	**83**	**37%**
	Dubai Government	**58**	**26%**
	Sharjah Government	**1**	**0%**
	Ajman Government	**0**	**0%**
	Umm Al Quwain Government	**1**	**0%**
	Ras Al Khaimah Government	**2**	**1%**
	Fujairah Government	**1**	**0%**
Gender	Male	**135**	**61%**
	Female	**88**	**39%**

Table 6- 4: Demographic Characteristics and Profiles of Survey Respondents (n=223) – continued

Variable	Category	Frequency	%
Job Area	Minister, Managing Director, CEO, Undersecretary , Chief Levels)	**15**	**7%**
	ICT	**26**	**12%**
	Operations (core business of organization)	**38**	**17%**
	Strategy, Business Excellence & Innovation	**49**	**22%**
	Processes & Quality Management	**0**	**0%**
	Customer Service	**13**	**6%**
	Communication & PR	**7**	**3%**
	Social Media	**6**	**3%**
	Legal Affairs	**9**	**4%**
	Internal Audit	**3**	**1%**
	Human Resources Management	**7**	**3%**
	Finance and Accounting	**0**	**0%**
	Procurement Management	**9**	**4%**
	Facilities & Security Management	**12**	**5%**
	Other	**9**	**4%**
Education Level	Doctoral Degree	**16**	**7%**
	Master's Degree	**76**	**34%**
	Bachelor's Degree	**127**	**57%**
	PG Diploma	**4**	**2%**
	Other	**0**	**0%**

Table 6- 4: Demographic Characteristics and Profiles of Survey Respondents (n=223) – continued.

Variable	Category	Frequency	%
Technological Turbulence	Our industry is characterized by rapidly changing technology	**58**	**26%**
	The rate of technology obsolescence is high in our industry	**47**	**21%**
	It is difficult to forecast the technological changes in the next three years	**36**	**16%**
	Technological changes provide big opportunities in our industry	**82**	**37%**
Kind of AI Technology(ies) Adopted	Natural Language Generation	**32**	**14%**
	Speech Recognition	**38**	**17%**
	Machine Learning Platforms	**67**	**30%**
	Virtual Agents (e.g. Chat bots)	**66**	**30%**
	Automated Decision Management	**45**	**20%**
	AI Optimized Hardware	**30**	**13%**
	Deep Learning Platforms	**49**	**22%**
	Robotic Process Automation	**46**	**21%**
	Text Analytics and Natural Language Processing (NLP)	**29**	**13%**
	Bio-metrics	**30**	**13%**
	Cyber Defense	**52**	**23%**
	Content Creation	**16**	**7%**
	Emotion Recognition	**17**	**8%**
	Image Recognition	**34**	**15%**
	Marketing Automation	**20**	**9%**
	Manufacturing robots	**10**	**4%**
	Self-driving cars	**12**	**5%**
	Smart assistants	**32**	**14%**
	Other	**5**	**2%**

6.4.4 Descriptive Statistics

The survey questions measured the participants' perceptions in relation to the identified constructs and relevant items using ordinal seven-point Likert-scales, the sample size of the study was 223 (>= 200), and the descriptive statistics of the results included the mean, standard deviation (SD), in addition to variance of each item in each construct were calculated and presented in *Appendix* B.

6.5 STRUCTURAL EQUATION MODELLING ANALYSIS

Byrne, (2010) considered Structural Equation Modelling (SEM) as a statistical tool comprising of a family of systems of equations (multivariate regression equations) which fall under linear models. SEM estimates multiple regression equations that are separate but interdependent to seek to explain the relationships among multiple variables simultaneously (Hair *et al.*, 2019). In this study SEM was adopted as a tool to conduct data analysis due to several reasons highlighted by Byrne, (2010); Hair *et al.*, (2019); and Tabachnick *et al.*, (2001) for example estimation of multiple interrelated dependence relationships, defining models with multiple constructs with different measurement items and explaining, ability to statistically test complex models, test through a Confirmatory Factor Analysis (CFA) model the relationships between constructs by using a structural model. Whereas, AMOS was used due to its ability to calculate goodness of fit for hypothesised models, the estimates to indicate statistical significance of constructs. In this research, three steps of examination were conducted: first, the CFA first-order assessment, second, the CFA second-order assessment, and finally SEM.

6.5.1 Goodness-of-fit indices

In this study, a proposed model was introduced and before utilizing its outputs, the model should first be subjected to a multiple-fit indices tests in order to assess its goodness-of-fit (GOF) (Byrne, 2010) in other words it measures how well the theoretical structure represents reality based on the given data (Hair *et, al.*, 2019).

Hair *et al.*, (2019) categorized GOF indices into three main fit indices: First absolute fit indices, which measure of how well the model reproduces the observed data, and is measured by Chi-square Statistic (χ^2), normed chi square (CMIN/DF) and Root Mean Square Error of Approximation (RMSEA). Second, incremental fit indices which assess the degree the estimated model compares to some alternative baseline model (or a null model) and is measured by Incremental Index of Fit (IFI), Tucker-Lewis Index (TLI) and Comparative Fit Index (CFI). Third, parsimonious fit indices which provide information about which model among several competing models is best, and are measured by CMIN/DF and IFI. (Table 6-5) summarises the recommended level of goodness-of-fit measures used in this study.

Table 6- 5: Goodness-of-fit Statistics in SEM

Index	Abbreviation	Type of fit measure	Recommended value of good-fit of the model	References
Chi-square	χ^2	Model fit	χ^2, df, p >0.05	(Byrne, 2010; Hair *et al.*, 2019)
Normed chisquare	CMIN/DF	Absolute fit and parsimony of model	1.0< χ^2 /df <3.0	(Byrne, 2010; Joreskog, 1993; Hair *et al.*, 2019)
The IncrementalIndex of Fit	IFI	Incremental fit, parsimonyand sample size	$\geq$0.90	(Bentler, 1992; Byrne, 2010; Gerbing and Anderson, 1993)
Tucker-LewisIndex	TLI	Incremental fit	$\geq$0.90	(Byrne, 2010; Hu & Bentler, 1999)
Comparative FitIndex	CFI	Incremental fit	$\geq$0.90	(Byrne, 2010; Hair et al., 2019)
Root Mean Square Error ofApproximation	RMSEA	Absolute fit	$\leq$ 0.08 good fit	(Hair *et al.*, 2019)

6.5.2 Measurement Model

The measurement model covers seven constructs: Data Management (DM); Organizational Culture (OC); System Quality (SQ); Digital Organizational Culture (DOC): Actual Usage (AU); Organizational Performance (OP); Intention to Continue Usage (ITCU). These constructs were measured by 44 items (indicators) highlighted in Table 5-2 in section 5.4. Nevertheless, there is a need to conduct first-order and second-order CFA due to the fact that the Organizational Culture (OC) construct is evaluated through a set of four characteristics measured with sub-indicators for each OC character as highlighted in previous chapters; thus, OC has indirect link to those sub-indicators measuring the lower order level factors. Through using AMOS application, the measurement model was tested and analysed through CFA and other statistical relevant indices and estimates were examined. Table 6-6 summarises the statistics used in the analysis.

Table 6- 6: Summary of Statistics

Term	Measure	Rule of Thumb	References
Average Variance Extracted (AVE)	Construct Validity; Convergent Validity; Discriminant Validity	AVE ≥ 0.5	(Hair *et al.*, 2019; Byrne, 2010)
Construct Reliability	Internal Consistency; Reliability	Estimates value ≥ 0.7	(Byrne, 2010; Hair *et al.*, 2019; Field, 2009)
Covariances	Construct Validity; Nomological Validity	Estimates are positive and significant	(Hair *et al.*, 2019; Field, 2009)
Correlations	Construct Validity; Nomological Validity	Estimates are positive and significant	(Hair *et al.*, 2019; Field, 2009)
Critical Ratio (C.R.)	Hypothesised Relationships and path analysis	Estimates value ≥ 1.96	(Hair *et al.*, 2019; Kline, 2015)
Cronbach's Alpha	Internal Consistency; Reliability	Estimates value ≥ 0.6	(Byrne, 2010; Hair *et al.*, 2019; Field, 2009)
Standardised Regression Weights	Factor Loadings; Construct Validity; ConvergentValidity	Estimates value ≥ 0.5	(Hair *et al.*, 2019; Byrne, 2010)
DescriptiveStatistics	Mean, Standard Deviation and Variance	demographic information and items analysis	(Byrne, 2010; Hair *et al.*, 2019; Field, 2009)

6.6 FACTOR ANALYSIS

Factor Analysis (FA) is a statistical method to enable researchers understand the structure set of items, and reduce the variables through extracting all their commonalities into a smaller number of factors (Hair *et al.*, 2019) and consequently simplify models with complex variables, which would eventually help in explaining the relationships between those constructs. Confirmatory Factor Analysis, is a model that analyses factors and focuses on the degree to which observed variables relate to latent factors and the relationship between factors and their measured variables (Byrne, 2010). A SEM model is tested for acceptability once it has been specified, according to Byrne (2010), SEM and statistical modelling in model-testing are used primarily to determine if a hypothesised model fits the sample data by determining its goodness-of-fit.

6.6.1 Confirmatory Factor Analysis

This research followed Anderson and Gerbing (1988) SEM two-step approach in conducting the quantitative analysis. Firstly, through using AMOS, the CFA is conducted to estimate the measurement model, then results are analysed for assessment for fit, that is how well the model under study accounted for the data based on one or more GOF indices and assess unidimensionality, convergent validity, and reliability of latent constructs. The second step is to test the confirmatory structural model which identifies the causal relationships between constructs as hypothesised by a research model.

The CFA was conducted to assess the measurement model by considering the goodness-of-fit indices, constructs validity, and constructs reliability of the measurement model. Due to the nature of the Organizational Culture construct; this research conducted first-order and second-order CFA tests in order to assess the measurement model.

6.6.2 First-order CFA model

The first order measurement model was set, then Maximum Likelihood Method for parameter estimation (MLE) was used to evaluate it. The results of the assessment are summarised in (Table 6-7). The results obtained for the initial model did not meet the minimum the values of GoF indices, indicating that the initial model needs refinement and further assessment to be conducted (Kline, 2015).

Table 6- 7: Goodness-Of-Fit Statistics for CFA Initial Model

Indices	χ^2	df	CMIN/DF	IFI	TLI	CFI	RMSEA
Standard			$1.0< \chi^2 /df <3.0$	≥ 0.90	≥ 0.90	≥ 0.90	≤ 0.08
Results	1162.817	704	1.652	0.894	0.88	0.892	0.054

Hair *et al.* (2019) and Byrne (2010) specified a set of criteria to be met in assessing the measurement model. AMOS analysis gives results of several estimates to be taken into consideration to help in improving the fitness of the model. This includes loading estimates, regression weights, standardised residuals and modification indices. Consequently, the analysis results were checked to identify problematic readings. After that being done, seventeen items were deleted from the model due to different reasons, for example, insignificant items with regression weights estimates greater than 0.05; Beta values less than 0.5; or standardised residuals greater than (2.5) or less than (-2.5) and so on.

Accordingly, a repeated process of removing items and retesting was conducted till the measurement model met the fit indices shown in Table 6-5 and scholars' recommendations Byrne (2010), Hair *et al.* (2019) and Kline (2015). Eventually, a total of 17 items dropped out from the model: (DM1, DM2, DM6, INV2, CNS1, CNS2, CNS3, CNS4, ADP1, MIS2, MIS4, SQ1, SQ6, OP1, OP4, OP6, and ITCU3). The results of the final revised CFA measurement model are presented in Table (6-8), where model's goodness-of-fit showed improvement, eventually, the final revised model demonstrated a better fit to the data. Table 6-8 presents the goodness-of-fit statistics of the CFA first-order measurement model.

Table 6- 8: Goodness-Of-Fit Statistics for CFA First-Order Model

Indices	χ^2	df	P	CMIN/DF	IFI	TLI	CFI	RMSEA
Standard				$1.0< \chi^2 /df <3.0$	≥ 0.90	≥ 0.90	≥ 0.90	≤ 0.08
Results	388.964	288	0	1.351	0.958	0.947	0.957	0.04

Looking at the results, all GoF measures achieved the recommended values, thus, confirmed that the measurement model fits the data adequately. The AMOS estimates results are attached in Appendix *B*.

The measurement model CFA first-order after the modifications is depicted in Figure 6-10.

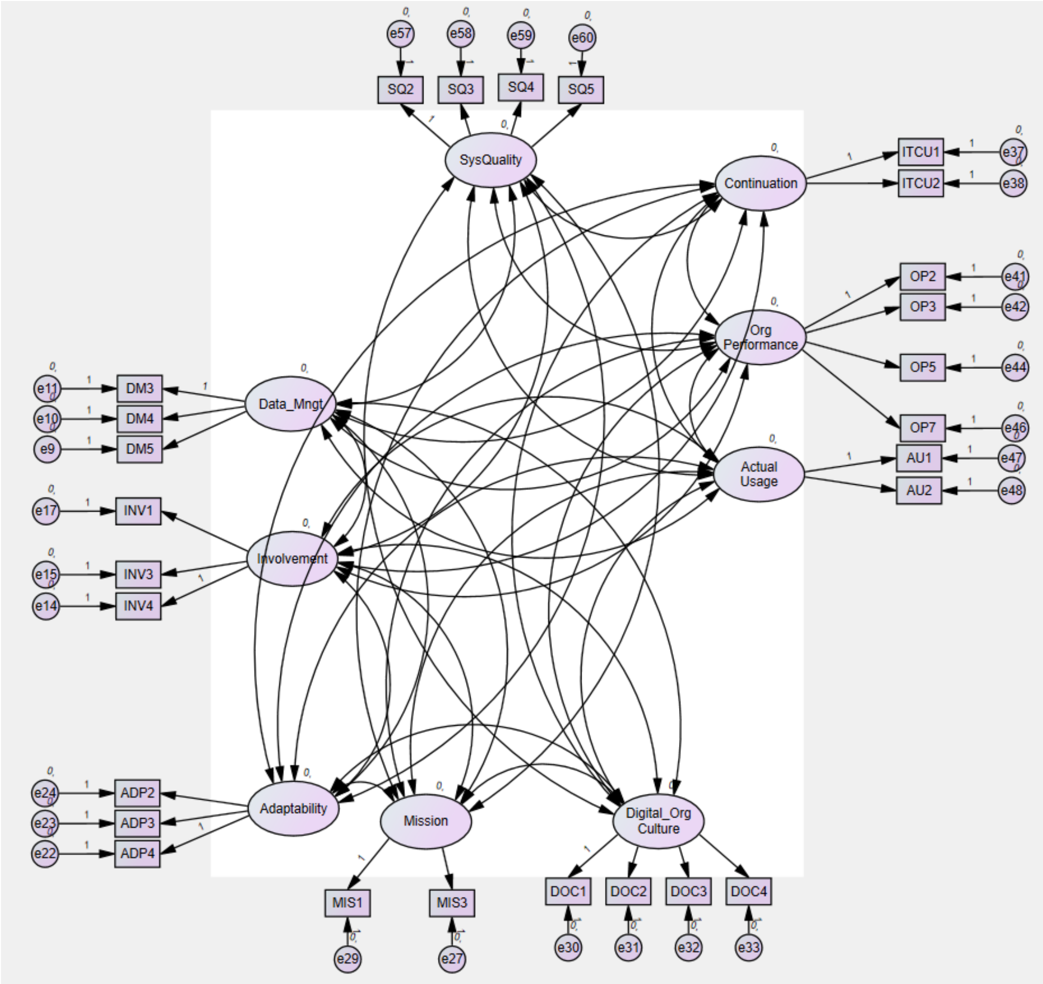

Figure 6- 10: CFA First-Order Model

6.6.2.1 CFA first-order Model Constructs Reliability

This is assessed through measuring both of the Cronbach's alpha reliability coefficient which determines and assess the internal consistency of each item in the survey., in addition to Construct reliability (CR) which measures internal consistency or the degree to which the measure of a construct is consistent or dependable; it is calculated for each construct in the model based on the square of the total of factor loadings for a construct using the formula suggested by Hair *et al.* (2018).

$$CR = \frac{(\sum_{i=1}^{n} \lambda_i)^2}{(\sum_{i=1}^{n} \lambda_i)^2 + (\sum_{i=1}^{n} \delta_i)}$$

Where,
λ is factor loadings (standardised regression weights)
i is total number of items
d is the error variance term for each latent construct

In general, an accepted construct reliability (CR) is ≥0.7, (Byrne, 2010; Hair *et al.*, 2019). Table 6-9 shows that all constructs in the model have internal consistency andadequate reliability.

Table 6- 9: Construct Reliability of CFA First-Order Model

Constructs	**Items**	**Cronbach's Alpha**	**Construct Reliability**
Data Management	3	**0.777**	**0.8**
Organisational Culture: Involvement (INV)	3	**0.719**	**0.7**
Organisational Culture: Consistency (CNS)	0		
Organisational Culture: Adaptability (ADP)	3	**0.744**	**0.7**
Organisational Culture: Mission (MIS)	2	**0.649**	**0.7**
System Quality (SQ)	4	**0.766**	**0.8**
Digital Organizational Culture (DOC)	4	**0.728**	**0.8**
Actual Usage (AU)	2	**0.821**	**0.8**
Organizational Performance (OP)	4	**0.799**	**0.8**
Intention to Continue Usage (ITCU)	2	**0.911**	**0.9**

6.6.2.2 CFA first-order Model Constructs Validity

Validity of a survey or questionnaire is concerned with assessing to what extent was the questionnaire measuring the phenomenon under study (Field, 2009). In this study, two tests are used to assess validity: convergent, and nomological validity.

6.6.2.2.1 Convergent Validity of CFA first-order model

In order to assess convergent validity of each construct, three factors need to be calculated: factor loadings of construct generated from AMOS; Average Variance Extracted (AVE); and Construct Reliability (CR). The following formula was used to calculate AVE (Hair *et al.*, 2019).

$$AVE = \frac{\sum_{i=1}^{n} \lambda_i^2}{n}$$

Where,
λ is factor loadings (standardised regression weights)
i is total number of items
n is the sample size

In general the values of factor loading, the AVE reliability, and standardised regression loading should be is ≥ 0.5, in order to meet the minimum accepted requirements. Looking at the output of AVE calculations listed in Table 6-10, the CFA First Order Model revealed a high level of convergent validity, as the standardised regression weights (factor loadings) ranged between (0.579 - 0.921) and all AVEs ranged between (0.5 - 0.8) which meet the minimum required criteria of results (≥0.5).

Table 6- 10: Convergent Validity of CFA First-Order Model

Constructs	Items	Standardised Regression Weights (Factor Loadings)	Average Variance Extracted (AVE)
AI System Quality (SQ)	SQ2	**0.579**	**0.5**
	SQ3	**0.731**	
	SQ4	**0.746**	
	SQ5	**0.641**	
Data Management (DM)	DM3	**0.694**	**0.5**
	DM4	**0.714**	
	DM5	**0.786**	
Organizational Culture: Involvement (INV)	INV1	**0.786**	**0.5**
	INV3	**0.725**	
	INV4	**0.692**	
Organizational Culture: Adaptability (ADP)	ADP2	**0.712**	**0.5**
	ADP3	**0.646**	
	ADP4	**0.742**	
Organizational Culture: Mission (MIS)	MIS1	**0.669**	**0.5**
	MIS3	**0.719**	
Digital Organizational Culture (DOC)	DOC1	**0.667**	**0.5**
	DOC2	**0.672**	
	DOC3	**0.714**	
	DOC4	**0.676**	
Actual Usage (AU)	AU1	**0.828**	**0.7**
	AU2	**0.865**	
Organizational Performance (OP)	OP2	**0.724**	**0.5**
	OP3	**0.693**	
	OP5	**0.660**	
	OP7	**0.751**	
Intention to Continue Usage (ITCU)	ITCU1	**0.921**	**0.8**
	ITCU2	**0.909**	

6.6.2.2.2 Nomological Validity of CFA first-order model

Hair *et al.*, (2019) noted that nomological validity examines the sense in the correlations between the constructs in the measurement model which means to be positive and significant. Therefore, AMOS construct correlations estimates can be used as a measure to assess the nomological validity of the model. Both of Table (6-11) and Table (6-12) show that all of the covariances and correlations estimates are meeting the requirements.

Table 6- 11: Covariances of CFA First-Order Model: (Group number 1 - Default model)

			Estimate	S.E.	C.R.	P
Data_Mngt	<-->	Involvement	0.157	0.036	4.355	***
Data_Mngt	<-->	Adaptability	0.142	0.036	3.906	***
Data_Mngt	<-->	Mission	0.147	0.034	4.332	***
Data_Mngt	<-->	Digital_Org_Culture	0.134	0.03	4.476	***
Data_Mngt	<-->	Continuation	0.144	0.044	3.299	***
Data_Mngt	<-->	Actual_Usage	0.266	0.045	5.905	***
Data_Mngt	<-->	Org_Performance	0.044	0.034	1.29	0.197
SysQuality	<-->	Data_Mngt	0.095	0.027	3.516	***
Involvement	<-->	Adaptability	0.26	0.041	6.3	***
Involvement	<-->	Mission	0.201	0.035	5.677	***
Involvement	<-->	Digital_Org_Culture	0.19	0.033	5.845	***
Involvement	<-->	Continuation	0.068	0.038	1.777	0.076
Involvement	<-->	Actual_Usage	0.135	0.035	3.923	***
Involvement	<-->	Org_Performance	0.12	0.034	3.509	***
SysQuality	<-->	Involvement	0.073	0.024	3.076	0.002
Adaptability	<-->	Mission	0.253	0.039	6.401	***
Adaptability	<-->	Digital_Org_Culture	0.167	0.031	5.393	***
Adaptability	<-->	Continuation	0.006	0.04	0.14	0.889
Adaptability	<-->	Actual_Usage	0.149	0.036	4.102	***
Adaptability	<-->	Org_Performance	0.053	0.033	1.586	0.113
SysQuality	<-->	Adaptability	0.104	0.027	3.894	***
Mission	<-->	Digital_Org_Culture	0.17	0.03	5.684	***
Mission	<-->	Continuation	0.035	0.036	0.981	0.327
Mission	<-->	Actual_Usage	0.097	0.031	3.087	0.002
Mission	<-->	Org_Performance	0.07	0.031	2.295	0.022
SysQuality	<-->	Mission	0.083	0.023	3.552	***
Digital_Org_Culture	<-->	Continuation	0.037	0.031	1.202	0.229

Table 6- 11: Covariances of CFA First-Order Model: (Group number 1 - Default model)

			Estimate	S.E.	C.R.	P
Digital_Org_Culture	<-->	Actual_Usage	0.095	0.027	3.484	***
Digital_Org_Culture	<-->	Org_Performance	0.061	0.026	2.326	0.02
SysQuality	<-->	Digital_Org_Culture	0.03	0.018	1.696	0.09
Continuation	<-->	Actual_Usage	0.224	0.046	4.857	***
Continuation	<-->	Org_Performance	0.375	0.055	6.847	***
SysQuality	<-->	Continuation	0.006	0.029	0.213	0.831
Org_Performance	<-->	Actual_Usage	0.05	0.035	1.435	0.151
SysQuality	<-->	Actual_Usage	0.073	0.026	2.857	0.004
SysQuality	<-->	Org_Performance	0.026	0.024	1.071	0.284

***** p< 0.01**

Table 6- 12: Correlations of CFA First-Order Model: (Group number 1 - Default model)

			Estimate
Data_Mngt	<-->	Involvement	0.453
Data_Mngt	<-->	Adaptability	0.382
Data_Mngt	<-->	Mission	0.474
Data_Mngt	<-->	Digital_Org_Culture	0.465
Data_Mngt	<-->	Continuation	0.278
Data_Mngt	<-->	Actual_Usage	0.651
Data_Mngt	<-->	Org_Performance	0.11
SysQuality	<-->	Data_Mngt	0.349
Involvement	<-->	Adaptability	0.787
Involvement	<-->	Mission	0.727
Involvement	<-->	Digital_Org_Culture	0.742
Involvement	<-->	Continuation	0.149
Involvement	<-->	Actual_Usage	0.372
Involvement	<-->	Org_Performance	0.336
SysQuality	<-->	Involvement	0.303
Adaptability	<-->	Mission	0.854
Adaptability	<-->	Digital_Org_Culture	0.609
Adaptability	<-->	Continuation	0.011
Adaptability	<-->	Actual_Usage	0.382
Adaptability	<-->	Org_Performance	0.139
SysQuality	<-->	Adaptability	0.401
Mission	<-->	Digital_Org_Culture	0.739

Table 6- 12: Correlations of CFA First-Order Model: (Group number 1 - Default model) continued

			Estimate
Mission	<-->	Continuation	0.086
Mission	<-->	Actual_Usage	0.297
Mission	<-->	Org_Performance	0.22
SysQuality	<-->	Mission	0.384
Digital_Org_Culture	<-->	Continuation	0.097
Digital_Org_Culture	<-->	Actual_Usage	0.316
Digital_Org_Culture	<-->	Org_Performance	0.206
SysQuality	<-->	Digital_Org_Culture	0.15
Continuation	<-->	Actual_Usage	0.414
Continuation	<-->	Org_Performance	0.709
SysQuality	<-->	Continuation	0.017
Org_Performance	<-->	Actual_Usage	0.119
SysQuality	<-->	Actual_Usage	0.256
SysQuality	<-->	Org_Performance	0.092

Consequently, assessment of the CFA first-order Model results showed that constructs used in the measurementmodel met the GOF criteria, and demonstrated adequate reliability and validity.

6.6.3 Second-order CFA Model

The OC is not measured directly, but is indirectly measured by those measuring lower order factors due to the lack of its own set of indicators. For this reason, second-order CFA model analysis is required to assess the model's goodness-of-fit. The same steps are used to assess the model's goodness-of-fit as for the first-order model. Figure 6-11, shows the tested CFA second-order measurement model

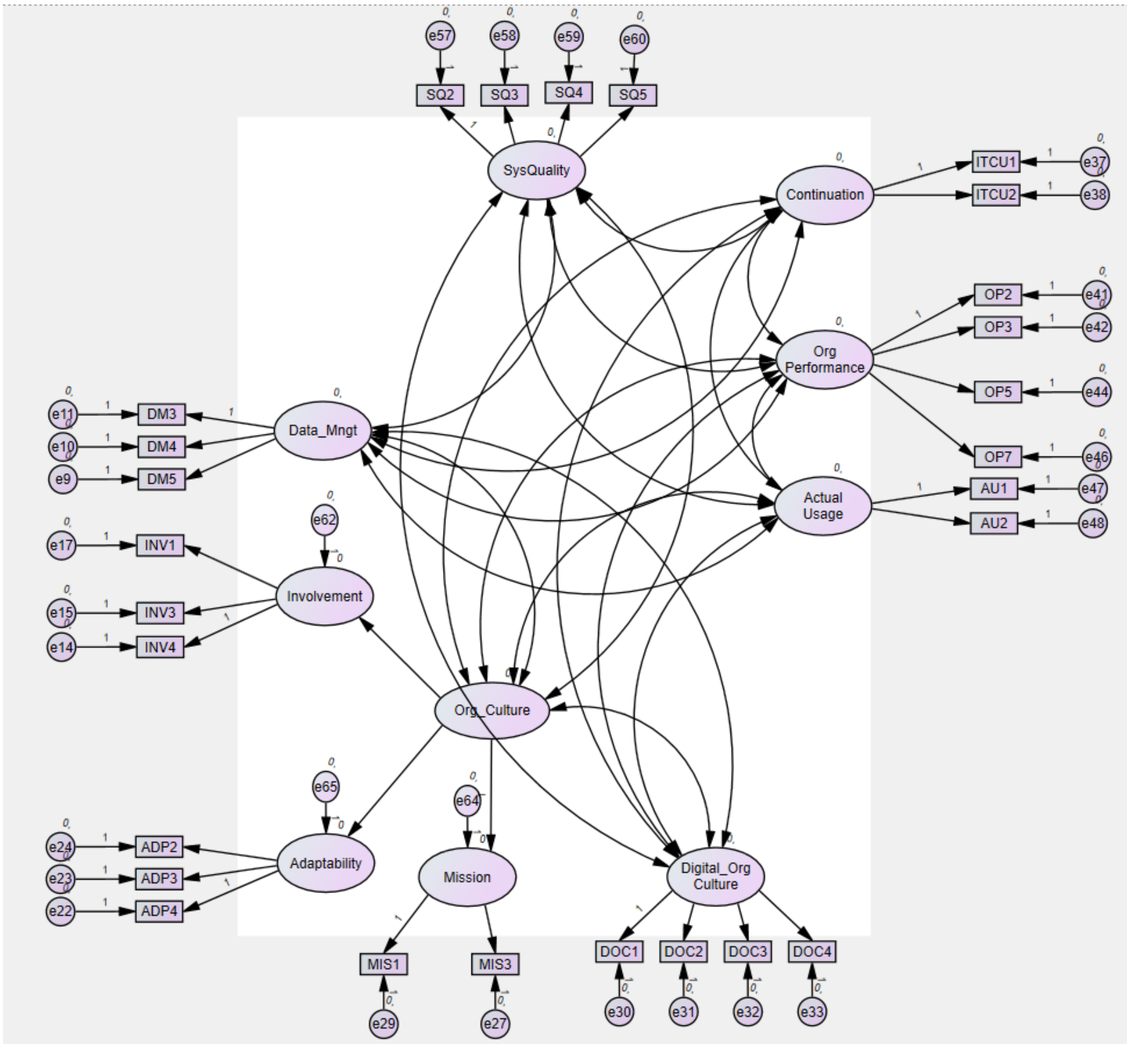

Figure 6-11: CFA Second-Order Model

Goodness-of-fit tests were conducted using AMOS for the CFA 2nd order measurement model. Results showed in Table 6-13 reveal that all indices meet the minimum goodness-of-fit requirements. In addition, results confirmed that the model adequately fits the data. Rest of AMOS estimates results are attached in *Appendix* B.

Table 6- 13: Goodness-Of-Fit Statistics for CFA Second-Order Model

Indices	χ^2	df	*p*	CMIN/DF	IFI	TLI	CFI	RMSEA
Standard				$1.0 < \chi^2/df < 3.0$	≥ 0.90	≥ 0.90	≥ 0.90	≤ 0.08
Results	413.118	300	0	1.377	0.952	0.943	0.951	0.041

6.6.3.1 CFA Second-order Model Constructs Reliability

In general, a good construct reliability value should be ≥0.7, which indicates that internal consistency exists. Nevertheless a value ≥ 0.6 is acceptable (Nunnally, 1978). Table 6-14 shows the values of internal consistency (ranging: 0.649-0.911) and adequate reliability (ranging: 0.8-0.9) for all constructs.

Table 6- 14: Construct Reliability of CFA Second-Order Model

Constructs	**Items**	**Cronbach's Alpha**	**Construct Reliability**
AI System Quality (SQ)	4	0.766	0.8
Data Management (DM)	3	0.777	0.8
Organizational Culture: Involvement (INV)	*3*	0.719	
Organizational Culture: Adaptability (ADP)	*3*	0.744	
Organizational Culture: Mission (MIS)	*2*	0.649	
All items of Organizational Culture (OC)	8	*0.843*	0.9
Digital Organizational Culture (DOC)	4	0.728	0.8
Actual Usage (AU)	2	0.821	0.8
Organizational Performance (OP)	4	0.799	0.8
Intention to Continue Usage (ITCU)	2	0.911	0.9
Total	27		

6.6.3.2 CFA Second-order Model Constructs Validity

As discussed in the CFA first-order Model Constructs validity, the same two tests convergent, and nomological validity are used for the CFA second-order model.

6.6.3.3 Convergent Validity of CFA second-order model

In general the values of factor loading, the AVE reliability, and standardised regression loading should be is ≥ 0.5, in order to meet the minimum accepted requirements. Looking at the output of AVE calculations listed in Table 6-15, the CFA second-order Model revealed a high level of convergent validity, as the standardised regression weights (factor loadings) ranged between (0.580 - 0.921) and all AVEs ranged between (0.5 - 0.8) which meet the minimum required criteria of results (≥0.5).

Table 6- 15: Convergent Validity of CFA Second-Order Model

Constructs	Items	Standardised Regression Weights (Factor Loadings)	Average Variance Extracted (AVE)
AI System Quality (SQ)	**SQ2**	0.580	0.5
	SQ3	0.729	
	SQ4	0.748	
	SQ5	0.641	
Data Management (DM)	**DM3**	0.698	0.5
	DM4	0.717	
	DM5	0.779	
Organizational Culture (OC)	**INV**	0.880	0.8
	ADP	0.880	
	MIS	0.907	
Digital Organizational Culture (DOC)	**DOC1**	0.667	0.5
	DOC2	0.672	
	DOC3	0.714	
	DOC4	0.676	
Actual Usage (AU)	**AU1**	0.828	0.7
	AU2	0.865	
Organizational Performance (OP)	**OP2**	0.724	0.5
	OP3	0.693	
	OP5	0.660	
	OP7	0.751	
Intention to Continue Usage (ITCU)	**ITCU1**	0.921	0.8
	ITCU2	0.909	

6.6.3.3.1 Nomological Validity of CFA second-order model

Tables 6-16 and 6-17 reveal that all of the estimates in the second-order are positive and significant.

As previously considered in the CFA first-order Model, AMOS construct correlations estimates can be used as a measure to assess the nomological validity of the model. Both of Table (6-16), and Table (6-17) show that all of the covariances and correlations estimates are meeting the requirements.

Tables 6-16: Covariances of CFA Second-Order Model: (Default model)

			Estimate	S.E.	C.R.	P
Data_Mngt	<-->	Digital_Org_Culture	0.137	0.03	4.506	***
Data_Mngt	<-->	Continuation	0.144	0.044	3.285	0.001
Data_Mngt	<-->	Actual_Usage	0.27	0.046	5.935	***
Data_Mngt	<-->	Org_Performance	0.044	0.034	1.281	0.2
Data_Mngt	<-->	SysQuality	0.095	0.027	3.507	***
Org_Culture	<-->	Data_Mngt	0.137	0.03	4.546	***
Digital_Org_Culture	<-->	Continuation	0.038	0.031	1.213	0.225
Digital_Org_Culture	<-->	Actual_Usage	0.099	0.028	3.527	***
Digital_Org_Culture	<-->	Org_Performance	0.061	0.026	2.33	0.02
Digital_Org_Culture	<-->	SysQuality	0.03	0.018	1.678	0.093
Org_Culture	<-->	Digital_Org_Culture	0.162	0.028	5.703	***
Continuation	<-->	Actual_Usage	0.228	0.047	4.892	***
Continuation	<-->	Org_Performance	0.374	0.055	6.832	***
Continuation	<-->	SysQuality	0.006	0.029	0.212	0.832
Org_Culture	<-->	Continuation	0.033	0.029	1.123	0.262
Org_Performance	<-->	Actual_Usage	0.051	0.035	1.453	0.146
Actual_Usage	<-->	SysQuality	0.072	0.026	2.782	0.005
Org_Culture	<-->	Actual_Usage	0.118	0.028	4.148	***
Org_Performance	<-->	SysQuality	0.026	0.024	1.08	0.28
Org_Culture	<-->	Org_Performance	0.074	0.026	2.849	0.004
Org_Culture	<-->	SysQuality	0.08	0.021	3.867	***

***** p < 0.01**

Table 6- 17: Correlations of CFA Second-Order Model: (Group Number 1 - Default Model)

			Estimate
Data_Mngt	<-->	Digital_Org_Culture	0.467
Data_Mngt	<-->	Continuation	0.277
Data_Mngt	<-->	Actual_Usage	0.65
Data_Mngt	<-->	Org_Performance	0.11
Data_Mngt	<-->	SysQuality	0.347
Org_Culture	<-->	Data_Mngt	0.489
Digital_Org_Culture	<-->	Continuation	0.097
Digital_Org_Culture	<-->	Actual_Usage	0.32

Table 6- 17: Correlations of CFA Second-Order Model: (Group Number 1 - Default Model) - continued

			Estimate
Digital_Org_Culture	<-->	Org_Performance	0.206
Digital_Org_Culture	<-->	SysQuality	0.149
Org_Culture	<-->	Digital_Org_Culture	0.779
Continuation	<-->	Actual_Usage	0.417
Continuation	<-->	Org_Performance	0.708
Continuation	<-->	SysQuality	0.017
Org_Culture	<-->	Continuation	0.089
Org_Performance	<-->	Actual_Usage	0.12
Actual_Usage	<-->	SysQuality	0.248
Org_Culture	<-->	Actual_Usage	0.399
Org_Performance	<-->	SysQuality	0.092
Org_Culture	<-->	Org_Performance	0.258
Org_Culture	<-->	SysQuality	0.409

Consequently, assessment results of the CFA second-order Model indicated that constructs used in the measurementmodel met the GOF criteria, and demonstrated adequate reliability and validity. Model and data were found to be unidimensional, therefore, no further refinement was required; in conclusion, and the model is confirmed to fit the data.

6.7 STRUCTURAL MODEL

Hair *et al.* (2019) considered the structural model as a representation of dependence relationships between the latent variables of the hypothesised model, this will enable the researcher to determine the degree of influence and its significance between the constructs. Table 6-18 shows the latent constructs used in the proposed conceptual model proposed in chapter 5, classified into two main categories (Exogenous and Endogenous constructs), in addition it shows the eight hypotheses (H1a, H1b, H2a, H2b, H3, H4, H5, and H6) that are represented by causal paths relationships. The proposed hypotheses will be tested using the statistical tool SEM.

Table 6- 18: Paths' Causal Relationships

Exogenous Constructs	**Endogenous Constructs**	**Hypothesis**	**Hypothesis Relationships (+)**
Data Management (DM)	System Quality (SQ) Digital Organizational Culture (DOC)	H1a H1b	DM → SQ DM → DOC
Organizational Culture (OC)	System Quality (SQ) Digital Organizational Culture (DOC)	H2a H2b	OC → SQ OC → DOC
System Quality (SQ)	Actual Usage (AU)	H3	SQ → AU
Digital Organizational Culture (DOC)	Actual Usage (AU)	H4	DOC → AU
Actual Usage (AU)	Organizational Performance (OP)	H5	AU → OP
Organizational Performance (OP)	Intention to Continue Usage (ITCU)	H6	OP → ITCU

Reference to the CFA first order and second order models results in the previous sections in which the measurement model revealed adequate GOF in all relevant indices, reliability in all relevant tests, and validity in both tests. Then fitness assessment using AMOS was conducted on model fit estimates, on Regression, Standard Regression Weights, Standardised Residual Covariance and others estimates, in addition to modification indices, which all showed the fitness of the model. Consequently, the second step in Anderson and Gerbing (1988) SEM two-step approach will be conducted to test the goodness-of-fit for the structure model and its hypotheses. This will follow the same steps used with the CFA model to evaluate the significance, values and direction of the structural parameter estimates.

6.7.1 Goodness-of-fit indices of structural model

To assess the hypothesised structural model, the GoF indices and other parameter estimates were examined, and the fit indices show that the hypothesised structural model delivered a good fit with the data. All of the measures used for the absolute fit and the incremental fit indicate goodness-of-fit of the model. Table 6-19 shows the statistical results of GoF of the structural model.

Table 6- 19: Goodness-Of-Fit Statistics of Structural Model

Indices	χ^2	df	*p*	CMIN/DF	IFI	TLI	CFI	RMSEA
Standard				$1.0< \chi^2/df <3.0$	≥ 0.90	≥ 0.90	≥ 0.90	≤ 0.08
Results	518.587	312	0	1.662	0.913	0.900	0.911	0.055

6.7.2 Hypothesis Testing

An important measure of determining whether a structural model is valid or not is to determine the coefficient parameters and the covariance matrix. Hair *et al.* (2019), stated that the parameter coefficient value is statistically significant at 0.05 levels when the Critical Ratio is higher than 1.96 for an estimate. The analysis parameter estimates are presented in Table 6-20, and *Appendix* B includes AMOS results.

Table 6- 20: Regression Weights of Latent Constructs

			Estimate	S.E.	C.R.	P
SQ	<---	DM	0.163	0.072	2.265	0.024
DOC	<---	DM	0.12	0.061	1.965	0.049
SQ	<---	OC	0.253	0.101	2.5	0.012
DOC	<---	OC	0.702	0.12	5.853	***
AU	<---	SQ	0.321	0.127	2.518	0.012
AU	<---	DOC	0.469	0.128	3.657	***
OP	<---	AU	0.212	0.08	2.645	0.008
ITCU	<---	OP	0.936	0.105	8.881	***

Note: *Estimate* = regression weight; *S.E* = standard error; *C.R* = critical ratio, *P* = significance value

Consequently, the results demonstrated that all t-values were above the 1.96 critical value; hypotheses H2b, H4, H5 and H6 causal paths' estimated Critical Ratio (t-value) were above the critical values at the significant value $p \leq 0.01$, whereas, H1a, H1b, H2a and H3 were above the critical value at the significant value $p \leq 0.05$. For example, taking the hypothesised relationship between Digital Organizational Culture (DOC) and Actual Usage (AU) with t-value of 3.657 (>1.96) was statistically significant at 1% level. Similarly, path between System Quality (SQ) and Actual Usage (AU) with t-value of 2.518 (>1.96) was statistically significant at 5% level. Final structural model with β values is presented in Figure 6-12.

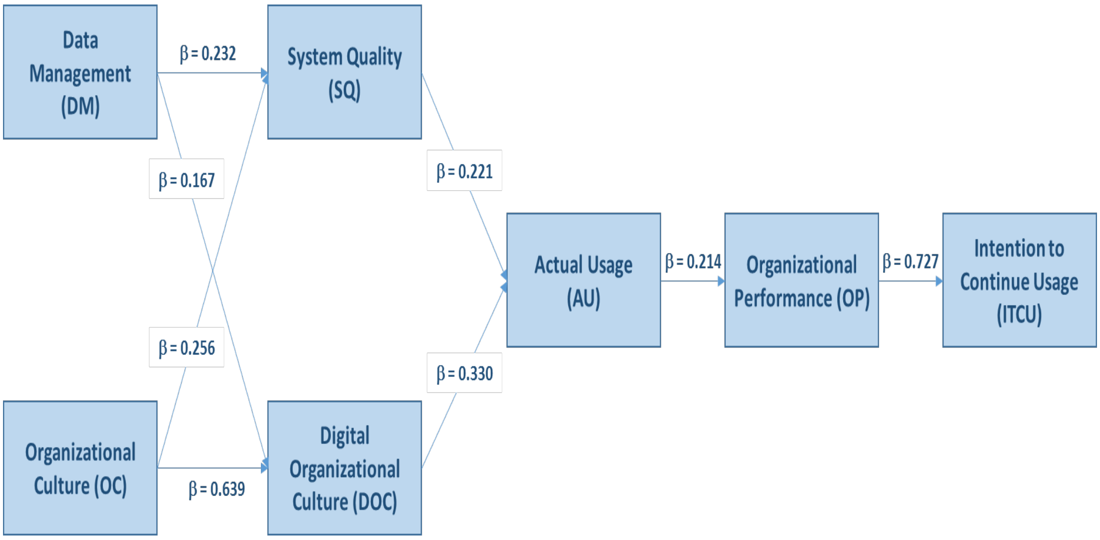

Figure 6- 12: Structural Model

In summary, the parameter estimate assessment's results indicated that all the eight hypothesised paths were positive (+) and significant. The standardised estimates for all hypotheses are statistically significant and show support for the hypotheses. Accordingly, all hypotheses were accepted. Table 6-21 shows the hypothesis testing final results.

Table 6- 21: Hypothesis Testing

Hypothesis	Hypothesis Relationships (+)	Standardised Regression Weights (β)	Supported
H1a: Data Management impacts positively the AI System Quality in Public Sector Organizations	DM → SQ	0.232	**YES ****
H1b: Data Management impacts positively the digital organizational culture in Public Sector Organizations	DM →DOC	0.167	**YES ****
H2a: Organizational Culture impacts positively the AI System Quality in Public Sector Organizations	OC → SQ	0.256	**YES ****
H2b: Organizational Culture impacts positively the digital organizational culture in Public Sector Organizations	OC → DOC	0.693	**YES ***
H3: System Quality impacts positively the Actual Usage in Public Sector Organizations	SQ → AU	0.221	**YES ****
H4: Digital Organizational Culture impacts positively the Actual Usage in Public Sector Organizations	DOC → AU	0.330	**YES ***
H5: Actual Usage impacts positively the Organizational Performance in Public Sector Organizations	AU → OP	0.214	**YES ***
H6: Organizational Performance impacts positively the Intention to Continue Usage in Public Sector Organizations	OP → ITCU	0.727	**YES ***

***p < 0.05; **p < 0.01**

To summarise, the structural model test results showed that the C.R. and P (significance value) and the standardised regression weights (**β**) indicated that all 8 hypotheses are positively significant and supported as shown in Tables 6-20 and 6-21,

H1a: Data Management impacts positively the AI System Quality in Public Sector Organizations.

The results in table (6-20) and table (6-21) show that the standardised regression weight (β) and critical ratio (t-value) for Data Management to AI System Quality is 0.232 and 2.265 respectively, which concludes that the hypothesised path is statistically significant, thus the results revealed strong support for hypothesis H1a, as highlighted in the proposed research model. This demonstrates that Data Management (DM) has a strong and positive significant effect on the AI system quality (SQ), implying that the better the data is managed, then the better the quality of the AI system will be in public sector organizations.

H1b: Data Management impacts positively the digital organizational culture in Public Sector Organizations.

The results in table (6-20) and table (6-21) show that the standardised regression weight (β) and critical ratio (t-value) for Data Management Digital Organizational Culture is 0.167 and 1.965 respectively, which concludes that the hypothesised path is statistically significant, thus the results revealed strong support for hypothesis H1b. This demonstrates that DM use as a construct has a strong and positive significant effect on DOC, indicating that the better the data is managed, then it will positively influence digital organizational culture in public sector organizations.

H2a: Organizational Culture impacts positively the AI System Quality in Public Sector Organizations.

The results in table (6-20) and table (6-21) show that the standardised regression weight (β) and critical ratio (t-value) for OC to SQ is 0.256 and 2.5 respectively Data, which concludes that the hypothesised path is statistically significant, thus the results revealed strong support for hypothesis H2a. This demonstrates that the organizational culture has a strong and positive significant effect on AI system Quality, indicating that the organizational culture positively influences system quality of AI technologies in public sector organizations.

H2b: Organizational Culture impacts positively the digital organizational culture in Public Sector Organizations.

The results in table (6-20) and table (6-21) show that the standardised regression weight (β) and critical ratio (t-value) for OC to DOC usage is 0.693 and 5.853 respectively, which concludes that the hypothesised path is statistically significant, thus the results revealed strong support for hypothesis H2b. This demonstrates that the organizational culture has a strong and positive significant effect on digital organizational culture, demonstrating that the organizational culture positively influences digital organizational culture in public sector organizations.

H3: System Quality impacts positively the Actual Usage in Public Sector Organizations.

The results in table (6-20) and table (6-21) show that the standardised regression weight (β) and critical ratio (t-value) for SQ to AU usage is 0.221 and 2.518 respectively, which concludes that the hypothesised path is statistically significant, thus the results revealed strong support for hypothesis H3. This reveals the AI System Quality has a strong and positive significant effect on AI systems Actual usage, indicating that the SQ positively influences AU in public sector organizations.

H4: Digital Organizational Culture impacts positively the Actual Usage in Public Sector Organizations.

The results in table (6-20) and table (6-21) show that the standardised regression weight (β) and critical ratio (t-value) for DOC to AU is 0.33 and 3.657 respectively, which concludes that the hypothesised path is statistically significant, thus the results revealed strong support for hypothesis H4. This reveals thedigital organizational culture has a strong and positive significant effect on actual usage, indicating that the DOC positively influences AU in public sector organizations.

H5: Actual Usage impacts positively the Organizational Performance in Public Sector Organizations.

The results in table (6-20) and table (6-21) show that the standardised regression weight (β) and critical ratio (t-value) for AU to OP is 0.214 and 2.645 respectively, which concludes that the hypothesised path is statistically significant, thus the results revealed strong support for hypothesis H5. This demonstrates that Actual Usage has a strong and positive significant effect on Organizational Performance, indicating that an increase in Actual Usage will positively influence organizational performance processes in public sector organizations.

H6: Organizational Performance impacts positively the Intention to Continue Usage in Public Sector Organizations.

The results in table (6-20) and table (6-21) show that the standardised regression weight (β) and critical ratio (t-value) for OP to ITCU usage is 0.727 and 8.881 respectively, which concludes that the hypothesised path is statistically significant, thus the results revealed strong support for hypothesis H6. This demonstrates that organisational performance has a strong and positive significant effect on Intention to Continue Usage, indicating that organisational performance positively influences ITCU in public sector organizations.

6.7.3 Control Variables

The influence of the four control variables; organization type, participant gender, job area, and technical turbulence, on the "Intention to continue usage" construct was tested as shown in Figure 6- 13 below.

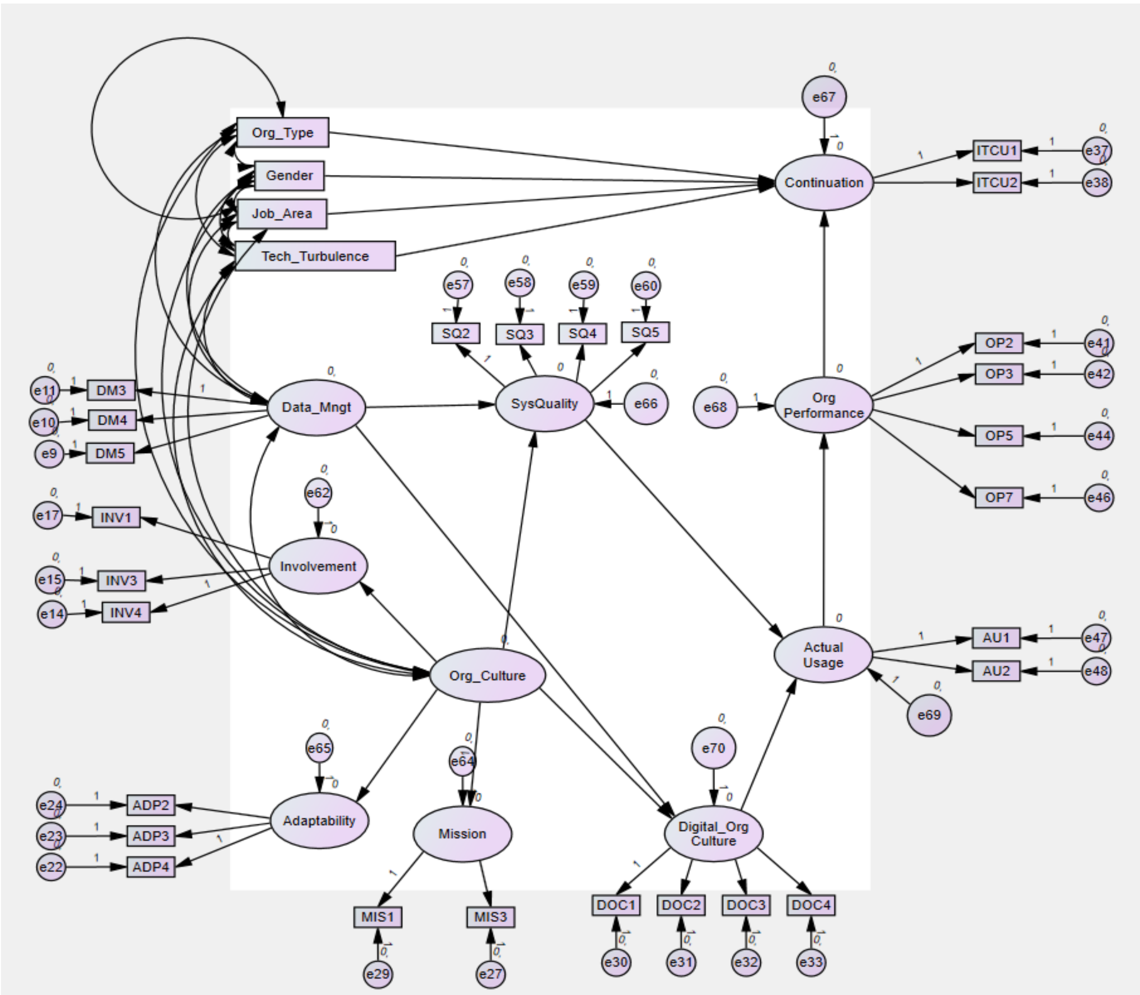

Figure 6-13 Structural Model with Control Variables.

As indicated in parameter estimates, the significance value (p) for all estimates were above 0.05, where organization type is 0.144, Gender of Participant is 0.3012, Job Area of Participant is 0.315, and Technical Turbulence in industry is 0.089, which showed that this is statistically insignificance, as show in Table (6-22) below.

Table 6-22 Control Variables Statistical Significance Test Results

			Estimate	S.E.	C.R.	P
ITCU	**<---**	**Org_Type**	.057	.039	1.463	.144
ITCU	**<---**	**Gender**	.096	.093	1.035	.301
ITCU	**<---**	**Job_Area**	.011	.011	1.005	.315
ITCU	**<---**	**Tech_Turbulence**	-.064	.038	-1.703	.089

6.8 CONCLUSIONS

This chapter presented the collected data analysis results of this study. The data collected was analysed statistically using different procedures, and followed by SEM through SPSS and AMOS. The normality of the data was investigated using descriptive statistics and the results demonstrated normal distribution of data. The study used the SEM method to test and examine the relationships between latent variables and their measures in the measurement model, and the relationships between latent variables in the structural model.

The measurement model fit was assessed through CFA first and second order models, and goodness-of-fit measures. The assessment results of CFA first-order measurement model revealed that the adjustments are needed, as some of the used fit indices results did not meet the acceptable limits. Hence, the measurement model was refined and seventeen items were deleted, and the CFA test was repeated; and the results of the revised model showed improvements in all the goodness-of-fit indices and exceeded the minimum acceptable limits, and revealed better fit to the data. This was followed by conducting the CFA second-order analysis to the items of the revised model in second order, and the results showed that the latent variables and their respective items used in the measurement model possessed adequate fit. According to the analysis results, the model fits the data, and does not require further tuning; as the measurement model and data were unidimensional.

The hypothesised model was assessed by using the structural model to test the relationships between the latent variables in accordance to the eight hypotheses. The analysis results demonstrated that the parameter estimates of the structural model showed that all of those eight hypotheses were statistically significant and supported and therefore the hypotheses were accepted.

The next chapter (7) presents the discussions of the main findings and analysis of the results.

CHAPTER SEVEN: DISCUSSION

7.1 INTRODUCTION

This main purpose of this chapter is to discuss comprehensively the findings that emerged from the data collected through the online questionnaire presented in chapter six, and to link the findings to research question and objectives, to both of the literature review, and the hypotheses introduced in the Conceptual Model in chapter 5.

This chapter presents the conceptual model and eight hypothesised relationships between the constructs, through discussing the results of each hypothesis.

7.2 THE CONCEPTUAL MODEL

An online self-completed questionnaire was administered to collect participants' opinions and judgements on the questions concerning the usage and intention to continue usage of AI technologies in the public sector organizations in the United Arab Emirates. As discussed in chapter 6, this questionnaire was designed by adapting applicable measures used in prior studies that tested in general areas of IS adoption models, and organizational culture, and in specific variables such as data management, organisational culture, digital organizational culture, system quality, IS actual usage, organizational performance, and intention to usage continuance. In this study, a total of 614 emails to fill the survey were sent, and 260 completed questionnaires were returned. However, 37 responses were discarded because 25 respondents replied back with "NO" to adopting AI in their respective organizations, and 12 replied with the same scale for all the items. Hence, the remaining 223 questionnaires were considered as the sample size and qualified for the data analysis process. The targeted participants represent employees in different federal and local governments in the UAE at different managerial levels and functions. The target population within the organizations were officials, employees and IT professionals, users, working in public sector organizations in the UAE who are already using AI technologies.

The study used multivariate statistical analysis to test the hypotheses, while Analysis of Moments Structures (AMOS) was used to visualise the measurement model, and to conduct CFA in addition to path analysis (testing the structural model). The regression weights of latent constructs estimates results showed that the critical ratio (C.R.) of the eight hypotheses were above the critical Z value ($Z=1.96$); H1b, H3, H5 and H6, at $p<1\%$ significant level, and H1a, H2a, H2b, H4 at p<5% significant level. Based on the analysis of standardised estimates for the eight hypotheses in the structural model test, the analysis results showed that those estimates (p-value, and C.R.) are statistically significant and (β values) supported the hypotheses. Subsequently, results of the model analysis concluded that the eight hypotheses were accepted. Each hypothesis testing and its main findings will be discussed separately in the next sections.

7.2.1 Data Management impact on the AI System Quality in Public Sector Organizations

The first hypothesis (H1a) in the model was that DM impacts positively the AI System Quality in Public Sector Organizations. After testing this hypothesis, the results came as follows (H1a: DM $\rightarrow$ SQ, $\beta = 0.232$, t-value = 2.265, $p < 0.05$). These results meant that there is a strong support for hypothesis H1a. This can be interpreted as data management has a strong and significant positive impact on SQ, implying that the better the data is managed, then the quality of the system will be positively influenced in Public Sector Organizations.

Numerous researchers from multiple perspectives analyze the impact of data management on IT system quality. In one of the studies, Beatrix (2022) made the fact evident that on the grounds of DeLone and McLean's (DM IS Success Model), data quality appeared as the measure of IT system Quality; this developed the linkage between the data management and IT system quality because the effective data management significantly minimized the potential errors in the data processing via essential policy-making for data utilization across different platforms in the organizational setting.

Furthermore, effective data management is highlighted as the crucial element in adequately deploying the IT System that facilitates the overall decision-making and strategic perspectives in the organizational setting (Liu & Chen, 2019). Correct deployment is also essential in the domain of overall system quality (Gunasekaran *et al.,* 2019). Additionally, Wiedenhoefer & Wiedenhoefer (2021) illustrated that data observability is an emerging process in data management confined to enhanced data quality and governance via complete data monitoring and insights development; the adaptability of the data observability significantly enhanced the IT system quality by real-time pipeline monitoring of the data integration. Thus, the relationship between data management and IT system quality appeared very positive.

7.2.2 Data Management impact on the Digital Organization Culture in Public Sector Organizations

The second hypothesis (H1b) in the model was that DM impacts positively the digital organization in the Public Sector Organizations. The estimates results of this hypothesis came as follows (H1b: DM → DOC, $\beta = 0.167$, t-value = 1.965, $p < 0.05$). These estimates demonstrated support for hypothesis H1b, and the hypothesis is accepted. This indicated that the management of data will positively influence the DOC in in Public Sector Organizations.

Data reliability was critically secured by data management, which allowed the organization to develop accurate alignment with the modification of the cultural needs and technological integration that consequently impacted the overall digital culture in the most positive manner. In light of the Denison Culture Model, it was very evident that Mission and Consistency were crucial determinants in influential overall culture (El Rashied, 2022); in this direction, Cheng et al. (2019) extended that Database Management System is the most prolific type of Data Management System in the prospect of digital culture and recognized as the "*relational database management system*". It prominently organized the data into columns and rows, having adequate database records. Furthermore, Győrödi et al. (2020) also contributed to it by illustrating these Relational databases constructed around the rigid data model followed by SQL programming language, which critically influenced and supported the properties like; atomicity and consistency that ultimately enhanced the digital transformation and digital integration, which significantly influenced the overall digital culture in the organization setting.

Moreover Tabrizi et al. (2019) stated that by the financial year of 2018, around 70% of the digital transformation initiatives ultimately failed due to faulty digital culture grounded on hindered collaborations and ineffective data management prospects. Contrary to this, Caro, Navarro and Ruiz (2020) presented the argument that Data Management is vital for digital culture because the technology integration and overall adaption of digital solutions within the digital culture primarily rely upon the digital data and its conversion into actionable business insights that are categorized as the key success factor of the overall digital culture. Hence on the grounds of these research-based pieces of evidence, the prospect is that effective Data management possesses a powerful impact on the overall digital culture in the organizational domain.

7.2.3 Organizational Culture impact on the AI system quality in Public Sector Organizations

In the proposed model, the third hypothesis (H2a) was that OC impacts positively the AI system quality in Public Sector Organizations. Testing of the hypothesis produced the following results (H2a: OC → SQ, $\beta = 0.256$, t-value = 2.500, $p < 0.05$). The estimates and β value demonstrated support for this relationship, as hypothesised in the research model. This indicated that OC influences AI SQ in public Sector Organizations as it has a strong and positive significant effect.

It was illustrated in the previous studies that organizational culture also influenced the IT System Quality and performance. Aboaoga, Aziz and Mohamed (2020) highlighted that IT System success is critically associated with the quality of the IT system and appears to be a significant determinant of success and productivity in the IT domain. In the exact alignment, Organizational Culture is a vital prospect that dictates the IT system performance by influencing the system's quality in the organizational settings. Adding more in the same dimension, Alqaraleh et al. (2022) established organizational Culture has an impact that is pronounced and significant in the prospect of IT system quality because the organizational Culture influences the development phase and proper implementation of that particular system.

Extending more towards it, Huynh (2021) contributed that the quality of the system critically defines the proper development and implementation of the IT system, and this implementation or development is based on some core factors, including the norms and power within the organization, identification and proper understanding of organizational values along with beliefs. The acceptable quality of the IT system required an effective and efficient strengthened Organizational Culture perfectly aligned with flexibility, quality, and customer orientation followed by performance orientation. Ideally, it is the management's responsibility to develop the working environment through organizational Culture that incorporated the implemented IT system in a quality manner (Wisna, 2015). Furthermore, on the grounds of "The DeLone and McLean Model of Information Systems Success", the system quality is critically measured on the grounds of; "ease-of-use, functionality, reliability, flexibility, data quality, portability, integration, and importance" and Organizational Culture statistically influenced all of these core factors (Binh et al., 2022);

thus it was evident enough that organizational culture possessed positive and significant impact over the quality of the IT system.

7.2.4 Organizational Culture impact on the Digital Organizational Culture in Public Sector Organizations

The fourth hypothesis (H2b), was OC impacts positively the DOC in Public Sector Organizations. Testing of the hypothesis produced the following results (H2b: OC → DOC, $\beta = 0.693$, t-value = 5.853, $p < 0.01$). These estimates demonstrated support for hypothesis H2b, and the hypothesis is accepted. This illustrated that OC significantly effects on DOC in Public Sector Organizations, and as stronger the OC in the organization the more DOC is impacted.

The digital organizational culture adequately describes the concepts and values about the interaction of technology and the internet with a corporate organizational workforce and crafted the behavioral aspects of human communication with technological advancements (Isensee et al., 2020). The digital organizational culture is the virtue of digital transformation, and in this direction, Caro, Navarro and Ruiz (2020) established the standpoint that solid organizational culture is significant for digital transformation because the influential organizational culture facilitates the leaders in developing a shared vision among the workforce in the organizational setting, affected the overall organizational growth and digital technology integration within the business culture.

Additionally, the research of Matos et al. (2019) proved the fact that collaborations were the critical element of the digital organizational culture as the workplace strategy in the modern dynamics, as the collaborative digital transformation or integration of technology improved the overall productivity by 20% and in the same direction Dubey et al., (2019) established that organizational culture impacted the collaborations as the inclusive organization culture; "promote the documenting and sharing of best practices so that they can make the most of everyone's expertise".

Moreover, Digital culture primarily relies upon high automation; though, the extensive higher degree of automation leads to the movement from a manual process to technology adoption. However, from a behavioral standpoint, humans are significantly reluctant towards mechanical change, which generated the need for high adaptability and involvement in an influential digital culture, as explained in Denison Culture Model (Vatan et al., 2022). It was already established by Lasrado & Kassem (2021) that the organizational culture primarily impacted the adaptability and involvement via empowering the stakeholders about the decision-making in the best possible manner. Thus all of these critical research facts made the impact of organizational culture evident over the Digital Organizational Culture.

7.2.5 AI System Quality impact on the actual use AI system in Public Sector Organizations

The fifth hypothesis (H3); SQ impacts positively the AU of AI related technologies in Public Sector Organizations. Testing of the hypothesis produced the following results (H3: SQ → AU,

β = 0.0.221, t-value = 2.518, $p < 0.05$). The estimates and β value demonstrated support for this relationship, as hypothesised in the research model. This is interpreted as the better the quality of the AI system in public sector organizations, the more frequent the actual usage of those system will be.

DeLone and McLean's (DM IS Success Model) critically established the association between the IS System Quality and System Use and indicated highlighted association between them as the system used was critically referred to as voluntary and constructed over the measured frequency of use, time of utilization, access and usage patterns followed by overall dependency (Mahmud *et al.,* 2022). In this all-important direction, Shim & Jo (2020) further elaborated the development of the DM IS Success Model based on the IS system and their impacts under which the model possessed three core constituents; "*the creation of a system, the use of the system, and the consequences of this system use*" even though all of the three components were essential, but not sufficient for the desired outcome as there would be no consequences associated with no system use, but even in the case of extensive system use if the system quality is poor or ill-mannered influenced the desired positive outcomes of the IT system usage.

Furthermore, in another prominent study, Yao *et al.* (2022) proved that the IS "system quality' is critically associated with IT system "use" and "net benefits." Thus the point is evident enough that IT system quality significantly impacts IS system use.

7.2.6 Organizational Digital Culture impact on the Use of the AI system in Public Sector Organizations

The sixth hypothesis (H4); DOC impacts positively the AU of AI technologies in Public Sector Organizations. Testing of this hypothesis produced the following (H4: DOC → AU, β = 0.0.330, t-value = 3.657, p <0.01). The estimates and β value demonstrated support for this relationship, as hypothesised in the research model. This means that the stronger the DOC in an organization the more the public sector organization will be using Ai related technologies.

Various research studies in the past have explored the impact of digital culture on IT system use. The best explanation of this association is established through the Technology-Organization-Environment (TOE) Framework. This framework ideally explained the adoption of technology in the organizational setting, providing the idea that technological adoption in the digital culture influenced technological, organizational and environmental contexts (Bryan & Zuva, 2021). Elaborating more towards this standpoint, Dzwigol *et al.* (2020) indicated that the organizations going through digital transformation by digitising their service delivery processes are likely to build networks with integrated technological structures, internally and with external stakeholders, to support the customer related processes; however, this prospect overall increased the pattern and utilization of IT systems influencing the use.

Furthermore, discussing the Organizational context within the TOE framework, the digital culture possessed the concept of Management via technology that is confined over; "*to demonstrate that the best results were obtained with the skills, experience and technology available to you throughout the project phases*" (Kane, 2019). In this very similar direction, Singh & Atwal (2019) also contributed that digital culture pivot the needs of IT system use while facilitating the leaders within the digital culture over the rapid communication with new integration and priorities, which critically supported the entire workforce towards the technological shift under the high IT system use. Thus, all of these facts cumulatively indicated the association between Digital Culture and IT system use.

7.2.7 Actual Usage of the AI system impact on the organizational performance in Public Sector Organizations

The seventh hypothesis (H5); AU of AI technologies impacts positively the OP in Public Sector Organizations. Testing of this hypothesis resulted in the following (H5: AU → OP, β = 0.0.214, t-value = 2.645, $p < 0.01$). The regression estimates and β value demonstrated support for this relationship and is accepted, as hypothesised in the research model. This means that the AU of AI technologies and OP are associated and that OP is influenced by the frequency and amount of AI system usage.

In one of the studies, Abdelwhab Ali *et al.* (2019) indicated via empirical evidence that IS system use and pattern of usage appeared as the most critical element in the dynamics of the modern user perspective. Even though IT system Accuracy and the availability of information are required for adequate IT system usage, on a holistic level, this IT system use influenced the utility and satisfaction of the user from a substantial level to a moderate level that made IT system as a potent channel of enhanced organizational performance.

Moreover, The DeLone and McLean Model also proposed that the elements of IT system use acted as a beneficial tool for the organization, especially in the domain of performance elevation (Jeyaraj, 2020). Additionally, (Abrego Almazán *et al.,* 2017) illustrated that the enterprises that were more concentrated towards the IS system, IS system quality and Information quality followed by IT system use increased the organizational outcomes that cumulatively increased the Organizational performance. Hence, IT systems possess a core association with organizational performance.

7.2.8 Organizational performance impact the intention to AI system usage continuance in Public Sector Organizations.

The last hypothesis (H6); OP impacts positively the ITCU in Public Sector Organizations. Testing of this hypothesis resulted in the following (H6: OP → ITCU, $\beta = 0.727$, t-value = 8.881, $p < 0.01$). The regression estimates and β value demonstrated strong support for this relationship and is accepted, as hypothesised in the research model. This means that the better the OP of the public sector organization the more inclined the intentions to continue usage of AI technologies are.

In one of the industries, Saeed Al-Maroof *et al.* (2020) highlighted that intention to continue using Technology; "*to assemble a combination of specialized individuals and heterogeneous* *assets in order to create and capture value for the firm through collaborative exploration and experimentation*". One of the profound researches in the recent course of the pandemic conducted by Li *et al.,* (2021) explored the relationship between Organizational Performance and Intention to continue using Technology on the grounds of exploring various prospects like; organizational commitment (OCM) and entrepreneurial orientation (EO) followed by growth mindset (GM). This study's results indicated that enhanced organizational performance possessed a positive relationship to the use of Technology because ICT appeared as the primary constituent for elevating the OCM and GM. However, the same study indicated that EO possessed insignificant association with ICT adoption, eliminating the important significant influence (Li *et al.,* 2021). Despite these contrary results, the influence of organizational performance is substantial over the intention towards the continued use of Technology.

Additionally, in a critical study, Haseeb *et al.* (2019) illustrated that the adoption of technology boosted the overall production efficiency, competitive pricing achievement and enhanced services provision; all of these properties ensured the provision of competitive advantage to the organization, and this acquisition of competitive advantage elevated the organizational performance via technology integration. In this manner, the prospect influenced the behaviour of business leaders towards the technology that vitally facilitated the intention to continue the technology integration. Thus, the organizational performance influenced the intention towards continued technology usage.

7.1 CONCLUSION

The purpose of this chapter was to present key findings regarding the factors that impact AI technologies Intention to Continue Usage in Public Sector Organizations, and discuss the assessment results of the significance impact of the hypothesised relationships between the DM, OC, SQ, DOC, AU, OP, and ITCU.

In this study, the sample size studied was for participants who all used AI technologies frequently in their respective public sector organizations. The sample understudy represented different federal and local government entities in the UAE.

It is worth to mention that the hypothesised model was successful in explaining the relationships between identified constructs in the structural model, and the analysis of the significant estimations (estimate, C.R. and P value) in regression weights of latent constructs (DM, OC, SQ, DOC, AU, OP, and ITCU) in addition to Beta value indicated that the eight hypotheses proposed in this study are statistically significant, and concluded that all hypotheses are accepted.

The next chapter will present the conclusions of this thesis.

CHAPTER EIGHT: CONCLUSIONS

8.1 INTRODUCTION

This chapter outlines the main contributions of this researched conducted in this thesis. This study's main aim was to examine the constructs affecting the usage of Artificial Intelligence (AI) related technologies, the impact on organizational performance, and then the intention to usage continuance of AI system(s) in public sector organizations in the United Arab Emirates. The study achieved this aim through conducting a literature review, which was followed by analysing the reviewed articles and researches. A conceptual framework was identified with proposed factors deducted from this analysis.

Relationships between these identified factors were hypothesised, and a structural model was proposed to explore these relationships through using structural equation modelling (SEM) with the AMOS statistical package. This chapter presents a summary of the findings and main conclusions of this thesis, and its main theoretical and managerial implications, in addition to a highlight of the limitations of the study. Lastly, the chapter forwards recommendations for future research.

In summary, this research followed the structured research process activities depicted in Figure (8-1) below.

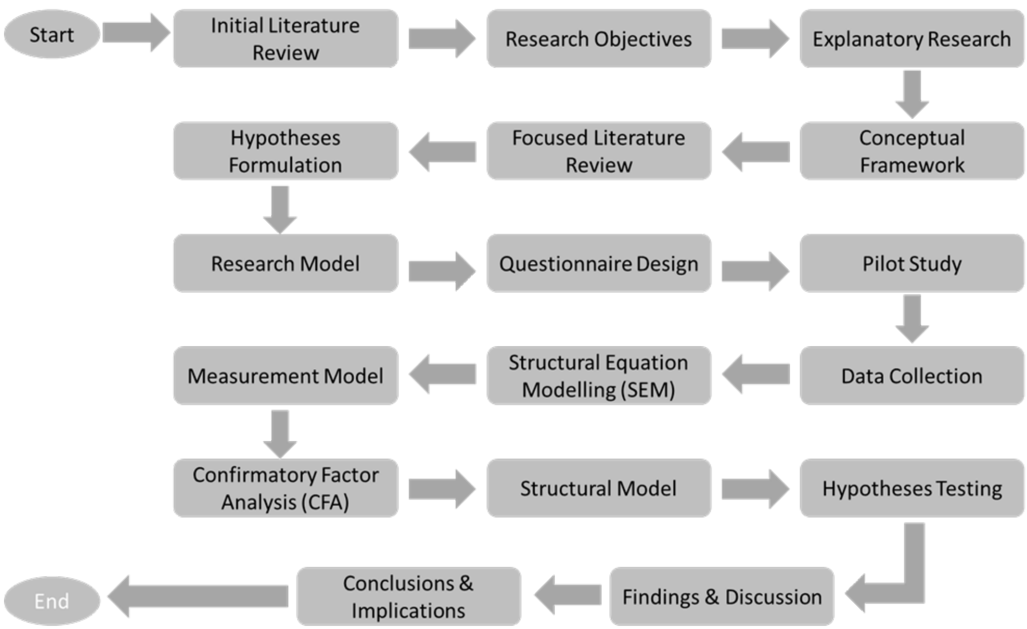

Figure 8- 1: Research Process Activities

8.2 SUMMARY OF THE STUDY AND RESEARCH FINDINGS

In summary, this study identified and examined a set of factors that influence the use and intention to continue usage of AI technologies in public sector organizations in the UAE. It has examined the following factors: data management, organisational culture, digital organizational culture, system quality, actual usage, organisational performance and intention to continue usage in public sector organizations in the UAE.

This section discusses how the key findings of the study achieved the three research objectives specified in the introduction chapter. The first objective "Identify an organizationally suitable technology adoption model with relevant constructs based on existing literature," is concerned with adopting technology model(s) on an organizational level. Therefore, existing theories and models, previously conducted studies and relevant literature were reviewed covering different aspects of concern, for example technology, data, organizational culture, IS actual usage, organizational performance, and intention to continue usage. As a result of these reviews, several factors that affected the usage and intention to continue using AI technologies were considered from different relevant models, which were then integrated in a hybrid model between DM IS Success Model and T.O.E. Framework. This hybrid model would assist in achieving the set research objectives and answering the research question based on the identified research gap in existing literature, in addition to identifying possibilities and providing recommendations for future research.

Addressing the second objective "Develop a conceptual model for the organizational intention to Artificial Intelligence technologies usage continuance in the public sector organizations in the United Arab Emirates", based on variables identified in the literature review, a conceptual model was proposed to explain the overall relationships between those identified variables. This model comprises seven constructs: organisational culture, data management, system quality, digital organizational culture, actual use, organizational performance, and intention to continue usage. Based on the literature review conducted, the study proposed eight hypothetical relationships between those seven constructs, and how they might influence each other.

The third objective was to "Test the validity of the conceptual model in the context of public sector organizations in the United Arab Emirates". To test the proposed conceptual model, an online survey was designed using the results of previous research, and utilizing scales and survey instruments that had been previously validated and verified. This study approached federal and local public sector organizations in the United Arab Emirates, targeting those who are already using AI technologies. In this study, organizations and employees were contacted electronically through emails, and professional networks; Linkedin, and consequently 223 completed questionnaires were used. This study used Structural Equation Modelling (SEM), and the Analysis of Moments Structures (AMOS) software, to test the measurement and structural model, and Confirmatory Factor Analysis (CFA) for 1st order variables followed by 2nd order variables were performed. Based on the results, the constructs utilized in the measurement model were found to have adequate reliability, convergence, and nomological validity. Next, the proposed structural model depicted in (Figure 6-11) was tested and the analysis results showed that the CR, P significance value, and β estimates for all eight hypotheses were statistically significant and revealed support for hypotheses (H1b, H3, H5 and H6, at 1% level, and H1a, H2a, H2b, H4 at 5% level).

The findings showed that both OC and DM have a positive and significant impact on SQ, with OC positive impact (r=0.256) slightly greater than DM (r=0.232). In addition, OC and DM have a significant positive impact on DOC, with a higher positive impact for OC (r=0.693) while DM (0.167). Taking other relationships, the test results revealed that both SQ and DOC significantly influence AU, as DOC has a greater positive impact (r=0.330) than SQ (r=0.221), the results showed significant influence of AU on OP (r=0.214), and then a high positive impact by OP on ITCU (r=0.727).

8.3 SUMMARY OF CONCLUSIONS

The literature review conducted in chapter 2, resulted in identifying a set of issues to which the results of this study provided significant answers. First, this study provides evidence of the relationships and positive influence between Artificial Intelligence system(s) usage, organizational performance, and intention to usage continuance of AI systems. Moreover, this study highlights the significance of both organizational culture and data management variables on digital organizational culture, in addition to the quality of AI system used in the organization, and consequently on the actual usage of the AI system(s).

Second, the study provides some insights on building a hybrid model with some variables from Delone and Mclean Information Success Model with Technology-Organization-

Environment (T.O.E.) Framework, and how that would help in understanding the adoption behaviour and usage of AI system(s); where data management and AI system quality variables were considered under the technology factors, and organizational culture and digital organizational culture were under the organization factors. The findings suggest that AI system actual usage is influenced by the system's quality in addition to the digital culture in the organization. The system actual usage impacts the organizational performance which consequently affects the intention to continue using the AI system.

Third, the results support the updated Petter *el al.,* (2013) Information System Success Model in that System Quality influences the usage of IS system; "Use" variable in Petter *et al.,* (2013) Model. Likewise, the findings support the positive significant relationship between IS use and Organizational Performance; which comprises one of "Net Benefits" two components in Petter *et al.,* (2013) Model.

Fourth, organizational culture played a significant role in the usage of AI systems in public sector organizations through its significant impact on both AI system quality variable and digital organization culture variable, which in turn impacted significantly the AI system usage. Organizations' management should pay more attention to organizational culture since it affects how people in the organization would react and adapt to organizational changes that are associated with the introduction and adoption of new technologies such as AI systems, in addition to the intention to continue using those new technologies.

Finally, digital organizational culture significantly impacted the AI system usage, therefore, organizations should give extra efforts to develop their digital culture, and not only their organizational culture. Public sector organizations need to build a shared digital strategy among all levels in the organization (Martinez –Caro *et al.,* 2020). DOC should be separated from organizational culture, as it had its own significant impact on AI system usage

8.4 CONTRIBUTIONS

This section discusses the main contributions and implications of this research, after the analysis and discussion of collected data, measurement model and structural model testing. These are categorized into theoretical and managerial, and are summarised in Table (8-1).

Table 8- 1: Summary of Main Research Contributions and Implications

Area	Summary of Main Contributions/Implications
Theoretical	• This study applied the extended DM IS Success Model and T.O.E. Framework in a new context of using AI systems in Public Sector Organizations in the UAE.
	• This study provides a model that examines the relationships between several factors that affect AI system usage and intention to continue using AI system(s) in Public Sector Organizations in the UAE, which distinguishes it from other existing empirical work.
	• This study tested and introduced a new conceptual framework that identified factors affecting AI system intention to usage continuance in Public Sector Organizations in the UAE.
	• This study enriched the literature related to AI systems adoption and usage, with the use of structural equation modelling with AMOS for testing both of the measurement and structural models.
	• This study contributed to the existing IS and AI usage literature, which will help public sector organizations in better understanding the variables that affect AI systems usage and intention to continue using such systems.
	• This study contributed to the literature by studying organization's digital culture as a separate variable from organizational culture, and studying the impact of organisational culture on organisational digital culture.
	• Easy to use tools were designed for reference; the theoretical framework, survey instrument, and the conceptual model which can be beneficial for other research or used in organisations.
Managerial	• The findings give beneficial insights to leaders, managers, AI system designers and data scientists in public sector organizations to better understand the intentions to use AI systems and continue using them.
	• An insight for public sector organizations to understand the factors affecting AI systems usage success, which will help them in prioritizing and utilizing their resources more effectively.

Table 8- 1: Summary of Main Research Contributions and Implications - continued

Area	Summary of Main Contributions/Implications
Managerial	• This study suggested OC and DOC as factors that affect AI systems adoption, usage and intention to continue using AI technologies. Thus, public sector organizations' leaders are recommended to nurture an "organisational culture" in general and "digital culture" in specific that enables employees at all levels to accept the new AI technologies.
	• This study resulted in proposing a new conceptual framework and model that would help directors, ICT specialists and programmers, and data scientists in identifying new ways to facilitate AI technologies adoption and usage.
	• The hybrid model proposed and tested in this study can benefit leaders in public sector organizations through assessing the status of implementation and identifying gaps or areas for improvements in their AI usage continuation Journey.
	• The model can be used to measure the maturity of identified variables' items across public sector organizations and develop organizational level plans to support high level decision makers in public sector organizations achieve the respective objectives and projects in the AI National Strategy.

8.4.1 Main Theoretical Contributions

This research offered an extent of significant theoretical contributions to the current body of literature in the field of AI adoption and usage in the public sector. First, this research integrated two different models; Delone and Mclean IS Success Model with T.O.E. Framework in a new context to use AI technologies and intend to continue using those technologies in public sector organizations in the UAE. In this hybrid model a new set of variables, i.e. organisational culture, data management, system quality, digital organizational culture, actual usage, organizational performance and intention to continue usage, which affects actual use of, and usage continuance intentions of AI technologies were integrated in one model. The results of the proposed model in this study identified the level of impact of those different factors on intention to continue using AI related technologies in the public sector organizations, and were successful in extending Delone and Mclean IS Success Model and T.O.E. Framework by understanding organizations' perceptions regarding organizational culture, digital culture, and data management, in addition to system quality, actual use, organizational performance, and intentions to continue usage in the context of AI related technologies.

Second, in this study, literature was reviewed and integrated from different organizational and technological perspectives. Generally, it was established that there is a sizeable body of literature which discusses AI, its history and technologies, and other literature that studies IS and technology adoption. Nevertheless, there is a gap in the existing literature on the use and intention to continue using AI technologies in organizations in general and in public sector in specific. Although several studies relating to AI have been conducted in areas of IS, ADM (another term used for AI), and government information, but there has not been to date any research which considered all of the set of seven variables tested in this research for intentions to continue usage of AI technologies in the public sector context.

Third, in this study a new conceptual framework, with factors that affect both of the usage, and of intentions to continue usage of AI technologies in public sector organizations in the UAE, was introduced and tested. The importance of this conceptual framework is reflected in its valuable contribution to IS, and AI technologies usage literature. This could assist public sector organizations identify new ways to facilitate AI technologies usage, and usage continuance through focusing on variables such as data management, organizational and digital cultures, in addition to quality of AI systems used.

Fourth, this study resulted in introducing new variables; data management, organizational culture and digital organizational culture to this new extended model, which was tested in the context of public sector in the UAE. In addition, the model contributed to the existing literature by introducing "intention to continue usage" construct to the two original theories; Delone & McLean IS Success Model and T.O.E. Framework.

Fifth, this study resulted in developing a model that examined the relationships between different variables: organisational culture; data management; digital organizational culture; system quality; actual usage; organizational performance; and intention to continue usage in public sector organizations in the UAE. This empirical study is different from other existing work on AI adoption and usage, due to the model and results obtained; this study examined a wider range of variables that affect the intention to continue usage of AI technologies.

The hybrid model developed in this research work extends existing theoretical models. Furthermore, this study generated conclusions and findings that will contribute to the understanding of the adoption and usage of AI technologies in IS and managerial fields.

Additionally, this research will generate original findings that will contribute to the relevant field of knowledge.

This empirical study methodologically contributed to the existing body of knowledge from two perspectives: firstly, through following a quantitative approach research in the public sector context in the UAE, where there limited number of quantitative studies on AI in the public sector organizations in the UAE, and secondly through introducing and using a new survey tool; an online questionnaire, as a method for examining variables impacting intentions to continue usage of AI technologies in the Public Sector Organizations in the UAE. There is scarcity in empirical quantitative research using online surveys that study the AI technologies usage and the intentions to continue using AI technologies in public sector organizations in the region in general and the UAE in specific, therefore this study is considered as one of the pioneering researches that cover this topic in the public sector context through introducing a new online questionnaire, and the first research to study the intentions to continue usage of AI technologies in the UAE public sector organizations.

This empirical study contributes by using a survey in a quantitative method, which resulted in valuable data for a study with participants from public sector organizations in the UAE, at different government functions, at different managerial and educational levels. In addition, in this research on AI technologies usage, the measurement and structural models were tested using sophisticated statistical tools such as structural equation modelling using the AMOS statistical package, which is not common in literature reviewed.

8.4.2 Main Managerial Implications

Different stakeholders, such as government officials, leaders and managers, and users in public sector organizations, in addition to AI system designers, data scientists and programmers can benefit from the many contributions and implications of this study, as discussed below.

Governments adopted technologies to enhance their processes and the ways they function or deliver services, and are currently investing in the usage of AI technologies, therefore having a better understanding of the factors influencing the successful adoption and usage of AI technologies is beneficial to them, as that will assist them to prioritise and allocate their resources more efficiently and effectively, and implement practices for example in data management, or instilling a proper and supporting organizational culture, or designing quality AI systems that would facilitate the digitisation journey.

The hybrid model proposed and tested in this study can benefit leaders in public sector organizations through assessing the status of implementation and identifying gaps or areas for improvements in the organizations against the set items and variables identified in this study, which would assist them in instilling strength areas and channelling efforts and resources on aspects which need more focus and attention, in order to achieve the desired performance levels.

On the government decision making level, AI concerned bodies can utilize the model to measure the maturity of identified variables' items across public sector organizations and develop organizational level plans to support public sector organizations achieve their respective objectives and projects in the AI National Strategy.

Public sector organizations are encouraged to consider both variables; organizational culture and digital organizational culture, when adopting AI technologies, through creating a working environment for its internal stakeholders, at all levels, that would facilitate the AI usage in the organization. The findings of the study suggested that the relationships between variables can be considered as determinants to the success of AI technologies usage and usage continuance intentions; OC had a significant impact on the AI System Quality, in addition to the digital organization culture which affects the organization's digitization journey. Both of those variables significantly impacted the actual usage of the AI system, which in turn had an impact on the organizational performance, which consequently influenced the organization's intention to continue using AI technologies.

Looking at AI technologies from development perspective, this study suggested the importance of data management and system quality in the use of AI technologies, therefore the IT specialists including AI systems developers and designers should take into consideration how they design databases, integrate them with different internal and external sources, how to share and cleanse data, in addition to designing accessible, easy to use and easy to understand systems that meet the needs and requirements of the intended users.

Besides the variables identified in this study, concerned managers, and IT specialists must not merely focus on the above mentioned factors; it is strongly recommended to consider other factors or parameters, which were not within the scope of this study for example own organization's specific context, national culture, organizational politics, technology or AI infrastructure readiness, and/or external pressure, which may have an influence on AI technologies usage and intention to continue usage.

In summary, the study proposed a model with variables that would assist public sector organizations in the UAE to identify new ways that would facilitate AI technologies usage and intention to continue using those technologies. This model offers advantages to decision makers and employees, such as:

- The model has been tested in public sector organizations with participants who represent different functions, different job levels, different educational backgrounds and levels, and different gender; male and female.
- The model introduced a different set of variables that distinguishes it from other existing empirical work on AI adoption and usage.
- The developed model consists of seven constructs, and each one of them includes a number of indices (27 in total), which were adapted from previous research.
- The model is aligned with intention to usage continuance which focuses on influence of organizational performance based on actual usage of AI technologies.
- The model focuses on organisational and managerial practices that are related to information technology success determinants, organisational culture, digital organizational culture, data management, system quality and actual usage of AI technologies, in addition to organisational performance. This will facilitate AI technologies usage in Public Sector organizations; which can be integrated with the organization's digital strategy and strategic initiatives, in addition to their own organizational capabilities.
- The survey covered federal and local public sector organizations across the seven emirates of United Arab Emirates (UAE).
- Easy to use questionnaire, and proposed model which can be applied by other studies or in organisations.
- The findings of the study give beneficial insights to decision makers in public sector organizations in the UAE to enhance AI technologies usage and intention to continue usage that would support the UAE's AI strategy and vision.

8.5 LIMITATIONS OF THE STUDY

The previous section presented the main contributions and implications of this study, and provided new perspectives to several issues in the literature. This study had its limitations, therefore, when interpreting the results and findings, it is important to keep the following recognised limitations, where other researchers can take into consideration in the future.

First, the study was conducted in federal and local public sector organizations in the UAE across different government functions. Clearly, despite the fact that the results obtained in this study have been significant, they cannot be generalized to other governments/public sector organizations in other countries.

Second, in this study, the sample size was (223) responses. This number even though it is (>200), nevertheless will have some effects on the generalisability of the findings, the model can be tested on larger samples to minimise the generalisability implications, or to enable building a SEM with more variables, for example to consider some of the neglected variables such as “consistency” in the organizational culture.

Third, AI adoption in organizations can be on a function level not across the organization, which can affect the number of respondents with AI technologies usage in their organizations.

Fourth, each organization has its own context and business factors, therefore it would not be reasonable to assume that OC, DM, DOC, SQ are the same in all public sector organizations in the UAE on both federal and local levels, as those organisations have different mandate and functional sectors, different strategic directions and goals, and uneven IT infrastructure readiness. Having said that, then the above mentioned limitations will turn into future research opportunities for researchers.

8.6 RECOMMENDATIONS FOR FURTHER RESEARCH

The main findings of this study answered the research question and the three research objectives, nevertheless throughout the literature review and data analysis, the researcher noticed additional interesting research areas which were not related to those objectives or question. Future research should pay greater attention to those notes and ideas, which could authenticate their generalizability.

Sample Size:

To generalize the findings and conduct significant analyses, further research needs to be conducted including a broader large-scale sample size for the same questionnaire.

Context:

Future research can expand the context of the study through including other public sector organizations in other countries, or testing and examining the research model in the context of other countries. This can add demonstrate the strength of the model across a variety of governments, which would enable conducting other types of studies for example comparative studies. It is recommended for future research to geographically expand the research model by testing it in different countries with different AI adoption maturity levels. Future researchers might also be interested in investigating and testing the research model developed in this study in a single public sector organization, including all of its geographical locations of operation.

Survey and Data:

Another recommendation would be concerning the span of data collection where in this study data was collected through a cross-sectional survey; whereas, it is recommended for future research to repeatedly collect data using longitudinal study. Future research could be using a combination of measure (subjective vs. objective) for measuring intention to AI technologies usage continuance instead of using subjective measures only.

The Model and Variables:

It is recommended that when conducting further research to expand the research model, which can be done through including additional variables from the literature review and conceptual framework, such as leadership support, IT infrastructure readiness, national culture, organizational AI culture and external pressure, which were excluded because of time and access to public sector organizations constraints.

Success vs. Failure:

It is recommended for future research to consider the failure aspects and reasons for not to use or continue using AI technologies in public sector organizations.

"This is has been an enlightening mind changing journey and as I reach to the end of this thesis, the new researcher is born"

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APPENDIX A

Pilot Survey Invitation Email

From: fares.dahabreh
To: ashraf.alnajdawi@ku.ac.ae
Subject: Online trial for my DBA survey
Date: Wednesday, February 9, 2022 8:33:11 AM

Dear Dr Al Najdawi.,

Greetings, my name is Fares Dahabreh, I am a DBA student at Newcastle Business School in Northumbria University Newcastle.

I am currently in the process of pursuing my data collection. I am writing a thesis on "*The Adoption of Artificial Intelligence in the United Arab Emirates Public Sector Organisations: An extended information system success model*". The aim of this research is to investigate and test the variables for adopting Artificial Intelligence that would enable public sector organizations in the United Arab Emirates adopt Artificial Intelligence related technologies successfully.

I am writing to you to kindly request your participation in ***an online trial run examination of my survey***. The purpose of this trial is to assist in fine-tuning of the survey and in identifying and eliminating potential problems before deploying the questionnaire to the intended participants. The survey instrument used in this study is entirely web-based. Participants will take the survey over the Internet using standard web browser software. I have outlined below some basic requests and instructions.

To complete the survey, kindly just click on the following link:
https://northumbria.onlinesurveys.ac.uk/ai-adoption-in-public-sector-03022022-v1

AI Adoption in Public Sector 03022022 v1

Online survey BOS

northumbria.onlinesurveys.ac.uk

Please read each question carefully and answer it. While some of you are experts in the subject, many of you may not be familiar with Artificial Intelligence Systems or related topics. Regardless of your level of expertise in the subject matter, I desire and appreciate your input. The goal of this trial run is not to gather subject-oriented data, but rather to refine the survey instrument. Please note the amount of time required to complete the survey and report it along with your comments to me by e-mail.

Online Questionnaire Invitation Email

From:	fares.dahabreh
To:	digitalajman@Ajman.ae
Subject:	Online Survey Participation in Doctoral degree thesis on AI Adoption in organizations - المشاركة في تعبئة استبيان رسالة دكتوراة حول تطبيق الذكاء الإصطناعي في القطاع الحكومي
Date:	Monday, March 21, 2022 1:35:44 PM

Dear Sirs,

Reference to our telephone call, kindly, allow me to introduce myself. My name is Fares Dahabreh, I am a Doctoral in Business Administration (DBA) degree student at Newcastle Business School in Northumbria University Newcastle.

I am writing a thesis on "*The Adoption of Artificial Intelligence in the United Arab Emirates Public Sector Organisations: An extended information system success model*". The aim of this research is to investigate and test the variables for adopting Artificial Intelligence that would enable public sector organizations in the United Arab Emirates adopt Artificial Intelligence related technologies successfully. I have already proposed some variables that affect adoption of AI based on renowned technology acceptance models, and I kindly need your opinion on those variables.

I am writing to you to kindly request your participation in an online survey. I would be very grateful if you and possibly several other people from your organization could participate in my research, therefore feel free to forward the survey to other colleagues. Your input is important to the success of this study, and your participation and your other colleagues will ensure that your organisation's views are represented.

Completing the survey will take approximately 15-20 minutes. You will just be asked to click on the answers. To complete the survey, kindly, just click on the following link:
https://northumbria.onlinesurveys.ac.uk/ai-adoption-uae

Please be assured that your response will be anonymous and used with complete confidentiality for research purposes only. At the end of this study, a copy of the final research report and conclusions will be available upon request.

This study and its protocol have received full ethical approval from Newcastle Business School at Northumbria University.

If you have any question regarding the research, please do not hesitate to contact with me by phone at +971 50 121 0964 or via e-mail at fares.dahabreh@northumbria.ac.uk.

Your time and assistance are greatly appreciated, and I look forward to having your participation in my research.

Thank you

Kind Regards,

Reminder

Reminder email

Greetings,,,

With reference to the my previous e-mail request regarding participation in filling out the DBA study questionnaire, I would like to thank you if you took the time and filled out the questionnaire.

The field of application of artificial intelligence is still new in the government sector in the world, and this research is considered an opportunity for government employees in the country to contribute to building a pioneering model for the factors of applying artificial intelligence in the government sector successfully so that it will be a business model developed in the United Arab Emirates and one of the first business models at the level the world.

I kindly ask you, if you have not filled out the questionnaire yet, to give me some of your time to fill out the questionnaire (approximately 20 minutes), and I also ask you to share the link with your colleagues at work, as well as with other employees in the government sector (federal or local) in the United Arab Emirates in order to They also fill out the questionnaire.

Kindly find below the link to the survey:

https://northumbria.onlinesurveys.ac.uk/ai-adoption-uae

I would like to remind you that the design of the questionnaire gives you the freedom to agree to participate in the study, and even after agreeing to participate, the questionnaire will ask whether you adopt artificial intelligence or not, and if you do not adopt one of the artificial intelligence technologies currently, the questionnaire will thank you and end, but if you adopt artificial intelligence, the questionnaire will move you to a survey Your opinion on the suggested factors that came out through scientific research, bearing in mind that the questionnaire does not ask to disclose any practices you have taken to adopt artificial intelligence techniques.

This is with an emphasis on the importance of maintaining the confidentiality and privacy of information and following scientific research protocols.

Thank you in advance for your help and time,

Fares Dahabreh
Doctoral in Business Administration (DBA) degree candidate
Newcastle Business School
Northumbria University Newcastle
Mobile: +971 50 1210964
email :fares.dahabreh@northumbria.ac.uk

Survey

AI Adoption in Public Sector Organizations

Introduction

Dear Sir/Madam,

Thank you for taking the time to complete this survey. Your answers are important to this study; this survey comprises of 4 parts that need to be answered. It is expected to take approximately 15 – 20 minutes to complete the survey. At the end of the survey you may leave your contact details, if you wish to receive a summary of the results of the survey.

The main purpose of this research is to examine the factors affecting the successful adoption of Artificial Intelligence (AI) in Public Sector Organizations (PSO) in the United Arab Emirates, with an aim of identifying and testing those potential variables that would enable PSO adopt and implement AI successfully.

This survey asks for your opinion or judgement, therefore there is no correct or incorrect answer. Kindly, respond to the survey based on your own judgement, and be assured that your response will be used for research purposes only, and that your details will be kept confidential and anonymous.

Your participation is highly appreciated, as it will assist in the success of this study. Kindly, proceed to next page to continue.

Thank you in advance.

Kind regards,

RESEARCH INDIVIDUAL INFORMED CONSENT FORM

Project Title: *The Adoption of Artificial Intelligence in the United Arab Emirates Public Sector Organisations: An extended information system success model.*

You are being invited to participate in this research as part of student DBA project. This is a synopsis of the project, the reasons for conducting it, and what it will entail. Kindly read through the below information carefully, and do not hesitate to contact the researcher for any clarifications needed.

Research Title: *The Adoption of Artificial Intelligence in the United Arab Emirates Public Sector Organisations: An extended information system success model*

This research will be conducted as part of a DBA degree in the Newcastle Business School at Northumbria University Newcastle, UK.

The aim of this research is to investigate and test the variables for adopting Artificial Intelligence that would enable public sector organizations in the United Arab Emirates adopt Artificial Intelligence related technologies successfully.

This study is going to be conducted through an online questionnaire and is expected to take 6-8 months for data collection and analysis.

Your participation will be through filling an online questionnaire that covers that factors affecting the adoption of Artificial Intelligence. The questionnaire will not take more than 15 – 20minutes of your time and is important to the success of this study.

The expected role of the organization's management is to fill in the online questionnaire and forward it to concerned functions to fill it in too (where applicable).

The participation is voluntary and you can withdraw freely at any time. All data collected is for the research purposes only, and will be analysed by the researcher under the observation of his designated supervisors. The data will always be treated with utmost confidentiality and kept anonymous and coded. A copy of the final research results and conclusions can be provided upon written request.

This study and its protocol have received full ethical approval from Newcastle Business School at Northumbria University.

Thank you in advance

Dear Participant (Volunteer):

If you would like to take part in this study, please read the statement below and tick 'Agree'

I understand the nature of the study, and what is required from me. I understand that after I participate I will receive a debrief providing me with information about the study and contact details for the researcher. I understand I am free to withdraw from the study at any time, without having to give a reason for withdrawing, and without prejudice.

I agree to provide information to the researcher and understand that my contribution will remain confidential. I also consent to the retention of this data under the condition that any subsequent use also be restricted to research projects that have gained ethical approval from Northumbria University.

I agree to the University of Northumbria at Newcastle recording and processing this information about me. I understand that this information will be used only for the purpose(s) set out in the information sheet supplied to me, and my consent is conditional upon the University complying with its duties and obligations under the Data Protection Act 2018 which incorporates General Data Protection Regulations (GDPR).

You can find out more about how we use your information at Privacy Notices

1. I would like to take part in this study.

○ Agree

Respondent's and Organization's Profile

2. Organization Name: (Optional)

3. Organization Type

- Federal Government
- Abu Dhabi Government
- Dubai Government
- Sharjah Government
- Ajman Government
- Umm Al Quwain Government
- Ras Al Khaimah Government
- Fujairah Government

4. Gender

- Male
- Female

5. Respondent's Job Area

5.a. If you selected Other, please specify:

6. Respondent's Education Level

6.a. If you selected Other, please specify:

7. Technological Turbulence, which is defined as "The rate of technological change in an industry"

- Our industry is characterized by rapidly changing technology
- The rate of technology obsolescence is high in our industry
- It is difficult to forecast the technological changes in the next three years
- Technological changes provide big opportunities in our industry

8. Does your organization adopt an Artificial Intelligence Technology/System? (Kindly, click on "More info" for examples of AI technologies)

More info

- Yes
- No
- I don't know
- We intend to in the future!

8.a. What kind of Artificial Intelligence technology(ies) is your organization using?

- [ ] Natural Language Generation
- [ ] Speech Recognition
- [ ] Machine Learning Platforms
- [ ] Virtual Agents (e.g. Chat bots)
- [ ] Automated Decision Management
- [ ] AI Optimized Hardware
- [ ] Deep Learning Platforms
- [ ] Robotic Process Automation
- [ ] Text Analytics and Natural Language Processing (NLP)
- [ ] Bio-metrics
- [ ] Cyber Defense
- [ ] Content Creation
- [ ] Emotion Recognition
- [ ] Image Recognition
- [ ] Marketing Automation
- [ ] Manufacturing robots
- [ ] Self-driving cars
- [ ] Smart assistants
- [ ] Other

8.a.i. If you selected Other, please specify:

Further clarifications

9. Kindly, select up to 3 top reasons:

Please select between 1 and 3 answers.

- [ ] I don't know what Artificial Intelligence System is
- [ ] Artificial Intelligence is complicated
- [ ] Artificial Intelligence System is too expensive
- [ ] We don't have Artificial Intelligence System in our organization
- [ ] Artificial Intelligence System does not fit our organization
- [ ] I don't know
- [ ] Other

9.a. If you selected Other, please specify:

Organization Dimension

10. **Organisational Culture:**

	With respect to your organisation, and using your own opinion and judgement, please state to what extent you agree or disagree with the following:						
	Strongly Disagree	Disagree	Somewhat Disagree	Neutral	Somewhat Agree	Agree	Strongly Agree
Decisions are usually made at the level where the best information is available	○	○	○	○	○	○	○
People work like they are part of a team	○	○	○	○	○	○	○
Teamwork is used to get work done, rather than hierarchy	○	○	○	○	○	○	○
There is continuous investment in the skills of employees	○	○	○	○	○	○	○

There is a clear and consistent set of values that governs the way the organization does business							
It is easy to reach consensus, even on difficult issues							
People from different parts of the organization share a common perspective							
It is easy to coordinate projects across different parts of the organization							
The way things are done is very flexible and easy to change							

New and improved ways to do work are continually adopted							
Customer input directly influences our decisions							
The organization makes certain that the everyone is informed about what is going on across the organization							
There is a long-term purpose and direction							
There is a clear strategy for the future							
There is widespread agreement about goals							

Leaders have a long-term viewpoint	○	○	○	○	○	○	○

11. **Digital Organizational Culture:**

More info

	With respect to your organisation, and using your own opinion and judgement, please state to what extent you agree or disagree with the following:						
	Strongly Disagree	Disagree	Somewhat Disagree	Neutral	Somewhat Agree	Agree	Strongly Agree
The teams collaborate functionally in the initiatives for the innovation and digital transformation	○	○	○	○	○	○	○
There is a clear orientation to digital technology changes inside the organization's culture	○	○	○	○	○	○	○

Technology Dimension

12. ***Artificial Intelligence System Quality:***

	Using your own opinion and judgement, please state to what extent you agree or disagree with the following:						
	Strongly Disagree	Disagree	Somewhat Disagree	Neutral	Somewhat Agree	Agree	Strongly Agree
The AI system is reliable	○	○	○	○	○	○	○
The AI system is user-friendly	○	○	○	○	○	○	○
The AI system is easy to use	○	○	○	○	○	○	○
The use of the AI system is easy to understand	○	○	○	○	○	○	○
The AI system provides convenient access	○	○	○	○	○	○	○
The AI system meets my requirements	○	○	○	○	○	○	○

The culture of digital innovation and change takes part as a natural process within the organization	○	○	○	○	○	○	○
The organization shares with the staff the digital strategy, taking into consideration their suggestions	○	○	○	○	○	○	○

13. **Data Management:**

	Using your own opinion and judgement, please state to what extent you agree or disagree with the following:						
	Strongly Disagree	Disagree	Somewhat Disagree	Neutral	Somewhat Agree	Agree	Strongly Agree
The organization has access to very large, unstructured, or fast-moving data for analysis	◌	◌	◌	◌	◌	◌	◌
The organization integrates data from multiple sources into a data warehouse for easy access	◌	◌	◌	◌	◌	◌	◌
The organization integrates external data with internal to facilitate analysis of business environment	◌	◌	◌	◌	◌	◌	◌
The organization has the capacity to share data across business units and organizational boundaries	◌	◌	◌	◌	◌	◌	◌
The organization is able to prepare and cleanse AI data efficiently and assess data for errors	◌	◌	◌	◌	◌	◌	◌
The organization is able to obtain data at the right level of details to produce meaningful insights	◌	◌	◌	◌	◌	◌	◌

AI System Adoption

14. **System Usage:**

	Using your own opinion and judgement, please state to what extent you agree or disagree with the following:						
	Strongly Disagree	Disagree	Somewhat Disagree	Neutral	Somewhat Agree	Agree	Strongly Agree
The organisation uses the AI system for work activities frequently.	○	○	○	○	○	○	○
The organisation uses the AI system a lot.	○	○	○	○	○	○	○

14.a.

	Using your own opinion and judgement, please state your AI system usage frequency:						
	Infrequently	Less than Once a month	Once a month	2 - 3 times a month	Once a week	2 - 3 times a week	Daily
With what frequency do you personally use AI systems in your organization?	○	○	○	○	○	○	○

15. **Organisational Performance:**

	Using your own opinion and judgement, please state to what extent you agree or disagree with the following:						
	Strongly Disagree	Disagree	Somewhat Disagree	Neutral	Somewhat Agree	Agree	Strongly Agree
Artificial Intelligence can provide us with more accurate data.	○	○	○	○	○	○	○
Artificial Intelligence can enhance Employee satisfaction.	○	○	○	○	○	○	○
Artificial Intelligence can enhance Quality of products and/or services.	○	○	○	○	○	○	○
I believe that Artificial Intelligence can enhance the organization's financial performance.	○	○	○	○	○	○	○
Artificial Intelligence can enhance the organization's operational performance.	○	○	○	○	○	○	○

Artificial Intelligence can increase customer satisfaction.	○	○	○	○	○	○	○
Artificial Intelligence resulted in improving business processes.	○	○	○	○	○	○	○

16. **Intention to AI System Usage Continuance (Post Usage Intentions):**

	Using your own opinion and judgement, please state to what extent you agree or disagree with the following:						
	Strongly Disagree	Disagree	Somewhat Disagree	Neutral	Somewhat Agree	Agree	Strongly Agree
Our organization intends to continue the use of AI system in the future.	○	○	○	○	○	○	○
Our organization intends to increase the use of AI systems in the future.	○	○	○	○	○	○	○
Our organization's intentions are to continue using the AI system than use any alternative means.	○	○	○	○	○	○	○

17. **Would you like to tell us anything else regarding your experience in AI System Usage in your organisation?**

Sharing of Research Results

18. If you would like to receive a copy of summary of results, please enter your contact information below *Optional*

- ◯ Yes, please
- ◯ Thank you, I am not interested

18.a. Title:

Please enter a response that only contains letters.

18.b. First Name:

18.c. Surname:

18.d. Email:

Please enter a valid email address.

Thank you

We thank you for your time spent taking this survey

Your response has been recorded

Key for selection options

5 - Respondent's Job Area

Minister, Managing Director, CEO, Undersecretary , Chief Levels)
ICT
Operations (core business of organization)
Strategy, Business Excellence & Innovation
Processes & Quality Management
Customer Service
Communication & PR
Social Media
Legal Affairs
Internal Audit
Human Resources Management
Finance and Accounting
Procurement Management
Facilities & Security Management
Other

6 - Respondent's Education Level

Doctoral degree
Masters degree
Bachelor's degree
PG Diploma
Other

Appendix (B): Descriptive Statistics of Construct Items and AMOS Output

Descriptive statistics of measured items of System Quality (SQ):

DESCRIPTIVES VARIABLES= SQ1 SQ2 SQ3 SQ4SQ5 SQ6

/STATISTICS=MEAN STDDEV VARIANCE MIN MAX.

	N	Minimum	Maximum	Mean	Std. Deviation	Variance
SQ1	223	2	7	5.82	.734	.538
SQ2	223	2	7	5.62	.755	.570
SQ3	223	2	7	5.75	.735	.540
SQ4	223	2	7	5.69	.789	.622
SQ5	223	2	7	5.75	.696	.484
SQ6	223	1	7	5.72	.882	.778
Valid N (listwise)	223					

Descriptive statistics of measured items of Data Management (DM):

DESCRIPTIVES VARIABLES= DM DM2 DM3 DM4 DM5 DM6

/STATISTICS=MEAN STDDEV VARIANCE MIN MAX.

	N	Minimum	Maximum	Mean	Std. Deviation	Variance
DM1	223	1	7	5.76	.916	.840
DM2	223	1	7	5.53	.889	.791
DM3	223	2	7	5.62	.901	.812
DM4	223	1	7	5.63	.906	.820
DM5	223	1	7	5.65	.950	.903
DM6	223	1	7	5.74	.883	.779
Valid N (listwise)	223					

Descriptive statistics of measured items of Organisational Culture (OC):

- Involvement (INV):

DESCRIPTIVES VARIABLES=INV1 INV2 INV3 INV4

/STATISTICS=MEAN STDDEV VARIANCE MIN MAX.

	N	Minimum	Maximum	Mean	Std. Deviation	Variance
INV1	223	3	7	5.78	.754	.569
INV2	223	4	7	5.68	.700	.490
INV3	223	3	7	5.75	.769	.592
INV4	223	3	7	5.68	.802	.643
Valid N (listwise)	223					

Descriptive statistics of measured items of Organisational Culture (OC):

- Consistency (CNS):

DESCRIPTIVES VARIABLES=CNS1 CNS2 CNS3 CNS4

/STATISTICS=MEAN STDDEV VARIANCE MIN MAX.

	N	Minimum	Maximum	Mean	Std. Deviation	Variance
CNS1	223	3	7	5.67	.825	.681
CNS2	223	3	7	5.62	.742	.551
CNS3	223	3	7	5.66	.800	.640
CNS4	223	3	7	5.68	.790	.623
Valid N (listwise)	223					

Descriptive statistics of measured items of Organisational Culture (OC):

- Adaptability (ADP):

DESCRIPTIVES VARIABLES= ADP1 ADP2 ADP3 ADP4

/STATISTICS=MEAN STDDEV VARIANCE MIN MAX.

	N	Minimum	Maximum	Mean	Std. Deviation	Variance
ADP1	223	2	7	5.59	.854	.729
ADP2	223	3	7	5.62	.835	.696
ADP3	223	3	7	5.61	.732	.535
ADP4	223	2	7	5.59	.805	.648
Valid N (listwise)	223					

Descriptive statistics of measured items of Organisational Culture (OC):

- Mission (MIS):

DESCRIPTIVES VARIABLES= MIS1 MIS2 MIS3 MIS4

/STATISTICS=MEAN STDDEV VARIANCE MIN MAX.

Descriptive Statistics

	N	Minimum	Maximum	Mean	Std. Deviation	Variance
MIS1	223	4	7	5.86	.740	.547
MIS2	223	3	7	5.89	.798	.637
MIS3	223	3	7	5.86	.779	.607
MIS4	223	3	7	5.94	.757	.573
Valid N (listwise)	223					

Descriptive statistics of measured items of Digital Organisational Culture (DOC):

DESCRIPTIVES VARIABLES= DOC1 DOC2 DOC3 DOC4

/STATISTICS=MEAN STDDEV VARIANCE MIN MAX.

	N	Minimum	Maximum	Mean	Std. Deviation	Variance
DOC1	223	3	7	5.79	.699	.489
DOC2	223	3	7	5.59	.729	.531
DOC3	223	2	7	5.70	.724	.525
DOC4	223	2	7	5.67	.797	.636
Valid N (listwise)	223					

Descriptive statistics of measured items of Actual Usage (AU):

DESCRIPTIVES VARIABLES= AU1 AU2

/STATISTICS=MEAN STDDEV VARIANCE MIN MAX.

	N	Minimum	Maximum	Mean	Std. Deviation	Variance
AU1	223	1	7	5.76	.801	.641
AU2	223	1	7	5.57	1.015	1.030
Valid N (listwise)	223					

Descriptive statistics of measured items of Organisational Performance (OP):

DESCRIPTIVES VARIABLES= OP1 OP2 OP3 OP4 OP5 OP6 OP7

/STATISTICS=MEAN STDDEV VARIANCE MIN MAX.

	N	Minimum	Maximum	Mean	Std. Deviation	Variance
OP1	223	1	7	6.30	.867	.752
OP2	223	1	7	6.03	.885	.783
OP3	223	1	7	6.26	.761	.579
OP4	223	1	7	6.13	.878	.771
OP5	223	1	7	6.22	.800	.641
OP6	223	1	7	6.17	.817	.667
OP7	223	1	7	6.29	.800	.640
Valid N (listwise)	223					

Descriptive statistics of measured items of Intention to Continue Usage (ITCU):

DESCRIPTIVES VARIABLES= ITCU1 ITCU2 ITCU3

	N	Minimum	Maximum	Mean	Std. Deviation	Variance
ITCU1	223	1	7	6.41	.901	.811
ITCU2	223	1	7	6.45	.883	.780
ITCU3	223	1	7	6.25	.904	.817
Valid N (listwise)	223					

First-order Regression Weights: (Group number 1 - Default model)

			Estimate	S.E.	C.R.	P
DM5	<---	Data_Mngt	1.194	0.128	9.351	***
DM4	<---	Data_Mngt	1.034	0.117	8.836	***
DM3	<---	Data_Mngt	1			
INV4	<---	Involvement	1			
INV3	<---	Involvement	0.988	0.111	8.908	***
INV1	<---	Involvement	0.855	0.106	8.042	***
ADP4	<---	Adaptability	1			
ADP3	<---	Adaptability	0.788	0.091	8.629	***
ADP2	<---	Adaptability	1.005	0.105	9.56	***
MIS3	<---	Mission	1.113	0.131	8.526	***
MIS1	<---	Mission	1			
DOC1	<---	Digital_Org_Culture	1			
DOC2	<---	Digital_Org_Culture	1.061	0.129	8.199	***
DOC3	<---	Digital_Org_Culture	1.129	0.131	8.622	***
DOC4	<---	Digital_Org_Culture	1.164	0.142	8.213	***
ITCU1	<---	Continuation	1			
ITCU2	<---	Continuation	0.97	0.055	17.587	***
OP2	<---	Org_Performance	1			
OP3	<---	Org_Performance	0.823	0.088	9.306	***
OP5	<---	Org_Performance	0.823	0.093	8.88	***
OP7	<---	Org_Performance	0.929	0.094	9.907	***
AU1	<---	Actual_Usage	1			
AU2	<---	Actual_Usage	1.349	0.118	11.478	***
SQ2	<---	SysQuality	1			
SQ3	<---	SysQuality	1.23	0.167	7.375	***
SQ4	<---	SysQuality	1.347	0.181	7.432	***
SQ5	<---	SysQuality	1.02	0.148	6.874	***

First-order Standardised Regression Weights: (Group number 1 - Default model)

			Estimate
DM5	<---	Data_Mngt	0.786
DM4	<---	Data_Mngt	0.714
DM3	<---	Data_Mngt	0.694
INV4	<---	Involvement	0.694
INV3	<---	Involvement	0.715
INV1	<---	Involvement	0.631
ADP4	<---	Adaptability	0.74
ADP3	<---	Adaptability	0.642
ADP2	<---	Adaptability	0.717
MIS3	<---	Mission	0.713
MIS1	<---	Mission	0.675
DOC1	<---	Digital_Org_Culture	0.661
DOC2	<---	Digital_Org_Culture	0.673
DOC3	<---	Digital_Org_Culture	0.72
DOC4	<---	Digital_Org_Culture	0.674
ITCU1	<---	Continuation	0.92
ITCU2	<---	Continuation	0.91
OP2	<---	Org_Performance	0.726
OP3	<---	Org_Performance	0.695
OP5	<---	Org_Performance	0.661
OP7	<---	Org_Performance	0.746
AU1	<---	Actual_Usage	0.82
AU2	<---	Actual_Usage	0.873
SQ2	<---	SysQuality	0.579
SQ3	<---	SysQuality	0.731
SQ4	<---	SysQuality	0.746
SQ5	<---	SysQuality	0.641

First-order Variances: (Group number 1 - Default model)

	Estimate	S.E.	C.R.	P
Data_Mngt	0.389	0.073	5.345	***
Involvement	0.309	0.058	5.353	***
Adaptability	0.353	0.06	5.865	***
Mission	0.248	0.049	5.014	***
Digital_Org_Culture	0.213	0.042	5.068	***
Continuation	0.683	0.081	8.471	***
Org_Performance	0.411	0.071	5.804	***
Actual_Usage	0.429	0.064	6.671	***
SysQuality	0.19	0.045	4.201	***
e9	0.344	0.052	6.559	***
e10	0.401	0.05	7.976	***
e11	0.42	0.051	8.262	***
e14	0.331	0.04	8.251	***
e15	0.288	0.036	7.939	***
e17	0.341	0.038	8.949	***
e22	0.292	0.038	7.758	***
e23	0.314	0.035	8.987	***
e24	0.337	0.041	8.133	***
e27	0.297	0.041	7.273	***
e29	0.297	0.037	8.044	***
e30	0.274	0.031	8.757	***
e31	0.289	0.033	8.635	***
e32	0.251	0.031	8.044	***
e33	0.345	0.04	8.619	***
e37	0.124	0.03	4.131	***
e38	0.134	0.029	4.613	***
e41	0.369	0.045	8.269	***
e42	0.298	0.034	8.642	***
e44	0.359	0.04	8.973	***
e46	0.282	0.035	7.972	***
e47	0.209	0.035	5.905	***
e48	0.244	0.058	4.185	***
e57	0.378	0.041	9.126	***
e58	0.25	0.035	7.213	***
e59	0.274	0.04	6.915	***
e60	0.284	0.033	8.563	***

First Order Model - Standardized Residual Covariances (Group number 1 - Default model)

	SQ5	SQ4	SQ3	SQ2	AU2	AU1	OP7	OP5	OP3	OP2	ITCU2	ITCU1	DOC4	DOC3	DOC2	DOC1	MIS1	MIS3	ADP2	ADP3	ADP4	INV1	INV3	INV4	DM3	DM4	DM5
SQ5	0																										
SQ4	0.607	0																									
SQ3	-0.595	0.12	0																								
SQ2	-0.263	-0.804	0.725	0																							
AU2	1.118	0.268	1.139	1.773	0																						
AU1	-0.561	-2.267	-2.182	0.606	0	0																					
OP7	0.556	0.345	0.546	1.384	-0.408	0.013	0																				
OP5	0.637	0.324	-0.169	0.219	-1.504	-1.41	1.091	0																			
OP3	-0.474	-0.832	-0.296	0.003	-0.069	0.924	0.225	-0.06	0																		
OP2	0.071	-1.135	-0.26	-0.143	0.715	1.636	-0.494	-0.41	-0.26	0																	
ITCU2	0.034	-0.905	0.05	1.086	-0.167	0.662	-0.226	-1.38	0.054	1.173	0																
ITCU1	-0.289	-0.374	0.55	0.563	-0.544	0.436	-0.472	-1.3	0.319	1.278	0	0															
DOC4	0.361	0.162	1.372	1.038	-0.72	-0.528	1.845	0.74	-0.15	2.385	1.187	0.147	0														
DOC3	1.456	-0.465	0.761	1.988	-0.343	0.488	-1.149	-0.36	-0.09	0.883	-0.04	-1.03	0.534	0													
DOC2	0.034	-1.305	-0.582	1.481	-0.235	0.997	-1.012	-1.13	-1.27	-1.24	-0.38	-2.26	-0.77	-0.08	0												
DOC1	-0.857	-1.52	-1.804	-0.543	-0.419	1.63	-0.38	-0.6	0.077	1.154	2.134	0.934	-0.02	-0.38	0.714	0											
MIS1	-0.237	-0.234	-0.109	0.146	-0.52	-0.022	0.198	0.578	-0.32	-0.29	0.381	0.436	1.671	-0.02	1.037	0.192	0										
MIS3	0.885	-0.063	-0.257	0.169	0.269	0.275	-0.341	1.546	-0.28	-0.64	0.331	-0.95	-0.63	-0.31	0.071	-1.57	0	0									
ADP2	-0.308	0.096	0.537	0.139	0.88	0.143	-0.729	0.29	0.205	-0.24	0.355	-0.28	-0.51	-0.78	0.493	-0.32	-0.58	0.774	0								
ADP3	0.542	0.961	0.361	0.837	-0.734	-0.964	-0.069	0.025	-0.32	0.93	0.064	0.356	0.305	-0.68	-0.63	-0.64	-0.67	-0.15	0.586	0							
ADP4	0.343	-1.216	-0.927	0.124	0.163	-0.184	0.054	0.026	-0.27	0.339	0.151	-0.44	1.093	0.335	0.371	0.46	0.063	0.159	-0.52	0.188	0						
INV1	-0.173	0.644	-1.023	1.678	-1.54	-0.487	-0.649	0.881	0.899	0.35	-0.07	-0.97	0.514	0.886	0.068	0.205	-0.16	0.057	0.359	0.126	0.465	0					
INV3	0.487	0.321	-0.085	1.244	-0.666	0.008	-0.587	-0.17	-0.98	-0.57	-0.49	-0.62	0.441	0.388	0.015	-0.14	0.423	0.003	-0.05	-0.71	0.63	-0.66	0				
INV4	-0.175	-1.118	-0.701	0.46	0.744	2.115	-0.907	0.916	0.593	1.33	0.896	1.152	-0.78	-0.23	-0.9	-0.36	-0.77	0.311	-0.43	-0.15	-0.32	0.136	0.41	0			
DM3	-0.558	-1.379	-0.609	0.864	-0.012	0.239	-0.341	0.218	0.915	-0.13	-0.12	-0.52	0.165	0.949	0.708	2.069	-0.18	0.726	1.866	0.175	0.196	0.257	1.201	1.352	0		
DM4	-0.29	-1.246	-0.072	1.604	-0.977	-0.521	-0.488	-1.03	-0.7	0.422	-0.32	-0.8	0.088	0.063	-0.36	0.317	-0.96	-0.31	0.052	-0.67	-0.59	-1.65	0.544	-0.36	0.518	0	
DM5	0.426	-0.102	0.434	2.163	0.782	0.073	0.309	0.021	-0.46	0.821	0.662	0.58	-0.74	-0.75	-0.49	-0.54	-0.3	0.674	0.811	-0.7	-0.87	-1.98	-0.11	0.545	-0.53	0.151	0

Second-order Regression Weights: (Group number 1 - Default model)

			Estimate	S.E.	C.R.	P
Involvement	<---	Org_Culture	1.089	0.151	7.214	***
Adaptability	<---	Org_Culture	1.17	0.155	7.549	***
Mission	<---	Org_Culture	1			
DM5	<---	Data_Mngt	1.176	0.126	9.328	***
DM4	<---	Data_Mngt	1.032	0.116	8.886	***
DM3	<---	Data_Mngt	1			
INV4	<---	Involvement	1			
INV3	<---	Involvement	1.005	0.114	8.804	***
INV1	<---	Involvement	0.847	0.108	7.829	***
ADP4	<---	Adaptability	1			
ADP3	<---	Adaptability	0.792	0.093	8.561	***
ADP2	<---	Adaptability	0.995	0.107	9.319	***
MIS3	<---	Mission	1.132	0.137	8.248	***
MIS1	<---	Mission	1			
DOC1	<---	Digital_Org_Culture	1			
DOC2	<---	Digital_Org_Culture	1.051	0.128	8.221	***
DOC3	<---	Digital_Org_Culture	1.109	0.129	8.596	***
DOC4	<---	Digital_Org_Culture	1.157	0.14	8.259	***
ITCU1	<---	Continuation	1			
ITCU2	<---	Continuation	0.968	0.055	17.545	***
OP2	<---	Org_Performance	1			
OP3	<---	Org_Performance	0.823	0.089	9.247	***
OP5	<---	Org_Performance	0.825	0.093	8.841	***
OP7	<---	Org_Performance	0.938	0.095	9.911	***
AU1	<---	Actual_Usage	1			
AU2	<---	Actual_Usage	1.323	0.117	11.32	***
SQ2	<---	SysQuality	1			
SQ3	<---	SysQuality	1.223	0.166	7.374	***
SQ4	<---	SysQuality	1.346	0.181	7.447	***
SQ5	<---	SysQuality	1.017	0.148	6.882	***

Second-order Standardised Regression Weights: (Group number 1 - Default model)

			Estimate
Involvement	<---	Org_Culture	0.88
Adaptability	<---	Org_Culture	0.88
Mission	<---	Org_Culture	0.907
DM5	<---	Data_Mngt	0.779
DM4	<---	Data_Mngt	0.717
DM3	<---	Data_Mngt	0.698
INV4	<---	Involvement	0.692
INV3	<---	Involvement	0.725
INV1	<---	Involvement	0.623
ADP4	<---	Adaptability	0.742
ADP3	<---	Adaptability	0.646
ADP2	<---	Adaptability	0.712
MIS3	<---	Mission	0.719
MIS1	<---	Mission	0.669
DOC1	<---	Digital_Org_Culture	0.667
DOC2	<---	Digital_Org_Culture	0.672
DOC3	<---	Digital_Org_Culture	0.714
DOC4	<---	Digital_Org_Culture	0.676
ITCU1	<---	Continuation	0.921
ITCU2	<---	Continuation	0.909
OP2	<---	Org_Performance	0.724
OP3	<---	Org_Performance	0.693
OP5	<---	Org_Performance	0.66
OP7	<---	Org_Performance	0.751
AU1	<---	Actual_Usage	0.828
AU2	<---	Actual_Usage	0.865
SQ2	<---	SysQuality	0.58
SQ3	<---	SysQuality	0.729
SQ4	<---	SysQuality	0.748
SQ5	<---	SysQuality	0.641

Second-order Variances: (Group number 1 - Default model)

	Estimate	S.E.	C.R.	P
Data_Mngt	0.394	0.073	5.38	***
Digital_Org_Culture	0.216	0.042	5.113	***
Continuation	0.684	0.081	8.477	***
Org_Performance	0.409	0.071	5.777	***
Actual_Usage	0.438	0.065	6.714	***
SysQuality	0.191	0.045	4.212	***
Org_Culture	0.2	0.044	4.56	***
e62	0.069	0.026	2.609	0.009
e64	0.043	0.025	1.724	0.085
e65	0.08	0.029	2.768	0.006
e9	0.353	0.053	6.678	***
e10	0.396	0.05	7.887	***
e11	0.415	0.051	8.172	***
e14	0.334	0.041	8.152	***
e15	0.28	0.037	7.628	***
e17	0.346	0.039	8.92	***
e22	0.29	0.038	7.547	***
e23	0.31	0.035	8.826	***
e24	0.342	0.043	8.045	***
e27	0.291	0.042	6.959	***
e29	0.301	0.038	7.989	***
e30	0.27	0.031	8.662	***
e31	0.29	0.034	8.604	***
e32	0.256	0.032	8.092	***
e33	0.343	0.04	8.56	***
e37	0.123	0.03	4.077	***
e38	0.135	0.029	4.632	***
e41	0.371	0.045	8.273	***
e42	0.299	0.035	8.643	***
e44	0.36	0.04	8.962	***
e46	0.278	0.035	7.872	***
e47	0.201	0.036	5.557	***
e48	0.259	0.059	4.382	***
e57	0.377	0.041	9.11	***
e58	0.252	0.035	7.251	***
e59	0.273	0.04	6.869	***

e60	0.284	0.033	8.557	***

Second-order Standardised Residual Covariances (Group number 1 - Default model)

	SQ5	SQ4	SQ3	SQ2	AU2	AU1	OP7	OP5	OP3	OP2	ITCU2	ITCU1	DOC4	DOC3	DOC2	DOC1	MIS1	MIS3	ADP2	ADP3	ADP4	INV1	INV3	INV4	DM3	DM4	DM5
SQ5	0																										
SQ4	0.595	0																									
SQ3	-0.572	0.131	0																								
SQ2	-0.275	-0.83	0.731	0																							
AU2	1.203	0.36	1.244	1.845	0																						
AU1	-0.52	-2.225	-2.129	0.638	0	0																					
OP7	0.547	0.333	0.538	1.374	-0.42	-0.02	0																				
OP5	0.633	0.317	-0.171	0.214	-1.508	-1.433	1.054	0																			
OP3	-0.477	-0.837	-0.297	-0.001	-0.071	0.902	0.2	-0.04	0																		
OP2	0.068	-1.14	-0.261	-0.147	0.713	1.613	-0.518	-0.38	-0.23	0																	
ITCU2	0.036	-0.904	0.052	1.087	-0.15	0.59	-0.252	-1.37	0.084	1.205	0																
ITCU1	-0.288	-0.373	0.552	0.563	-0.535	0.356	-0.509	-1.29	0.339	1.3	0	0															
DOC4	0.37	0.169	1.386	1.043	-0.738	-0.596	1.829	0.735	-0.15	2.383	1.177	0.135	0														
DOC3	1.477	-0.443	0.789	2.004	-0.327	0.449	-1.147	-0.34	-0.07	0.899	-0.04	-1.03	0.576	0													
DOC2	0.046	-1.294	-0.565	1.489	-0.243	0.938	-1.022	-1.13	-1.27	-1.23	-0.39	-2.27	-0.78	-0.02	0												
DOC1	-0.855	-1.52	-1.797	-0.543	-0.453	1.546	-0.405	-0.62	0.066	1.143	2.119	0.917	-0.1	-0.37	0.664	0											
MIS1	-0.134	-0.12	0.018	0.234	-1.02	-0.551	0.101	0.503	-0.4	-0.37	0.431	0.485	1.917	0.287	1.297	0.399	0										
MIS3	0.953	0.008	-0.171	0.224	-0.317	-0.338	-0.474	1.438	-0.38	-0.75	0.371	-0.91	-0.46	-0.07	0.259	-1.44	0	0									
ADP2	-0.012	0.435	0.887	0.403	1.223	0.403	-1.417	-0.31	-0.43	-0.89	-0.29	-0.94	-1.01	-1.25	0.004	-0.84	-0.13	1.169	0								
ADP3	0.777	1.23	0.637	1.045	-0.475	-0.774	-0.712	-0.54	-0.91	0.315	-0.53	-0.24	-0.22	-1.17	-1.13	-1.17	-0.33	0.123	0.584	0							
ADP4	0.628	-0.899	-0.6	0.375	0.481	0.053	-0.676	-0.61	-0.94	-0.36	-0.52	-1.12	0.518	-0.2	-0.18	-0.13	0.484	0.503	-0.48	0.126	0						
INV1	-0.484	0.276	-1.365	1.388	-1.314	-0.322	0.116	1.578	1.635	1.115	0.542	-0.36	0.899	1.353	0.464	0.556	-0.49	-0.37	0.536	0.219	0.6	0					
INV3	0.072	-0.167	-0.546	0.859	-0.49	0.116	0.232	0.567	-0.2	0.242	0.181	0.059	0.748	0.775	0.337	0.128	-0.09	-0.62	0.006	-0.74	0.631	-0.66	0				
INV4	-0.537	-1.539	-1.102	0.125	0.971	2.273	-0.085	1.668	1.384	2.163	1.562	1.825	-0.41	0.22	-0.52	-0.03	-1.17	-0.21	-0.29	-0.1	-0.23	0.233	0.345	0			
DM3	-0.563	-1.39	-0.605	0.855	0.008	0.156	-0.346	0.219	0.918	-0.13	-0.12	-0.52	0.117	0.939	0.672	2.001	0.03	0.899	1.509	-0.18	-0.19	0.417	1.301	1.502	0		
DM4	-0.292	-1.253	-0.065	1.597	-0.95	-0.598	-0.492	-1.03	-0.69	0.426	-0.32	-0.8	0.043	0.057	-0.39	0.253	-0.74	-0.13	-0.3	-1.03	-0.98	-1.49	0.65	-0.2	0.438	0	
DM5	0.46	-0.07	0.483	2.188	0.898	0.068	0.318	0.034	-0.45	0.838	0.704	0.617	-0.74	-0.71	-0.48	-0.56	-0.01	0.923	0.467	-1.05	-1.24	-1.76	0.051	0.764	-0.51	0.175	0

Structural Model - Regression Weights: (Group number 1 - Default model)

			Estimate	S.E.	C.R.	P
SysQuality	<---	Data_Mngt	0.163	0.072	2.265	0.024
Digital_Org_Culture	<---	Data_Mngt	0.12	0.061	1.965	0.049
SysQuality	<---	Org_Culture	0.253	0.101	2.5	0.012
Digital_Org_Culture	<---	Org_Culture	0.702	0.12	5.853	***
Actual_Usage	<---	SysQuality	0.321	0.127	2.518	0.012
Actual_Usage	<---	Digital_Org_Culture	0.469	0.128	3.657	***
Org_Performance	<---	Actual_Usage	0.212	0.08	2.645	0.008
Involvement	<---	Org_Culture	1.07	0.15	7.154	***
Adaptability	<---	Org_Culture	1.167	0.155	7.535	***
Mission	<---	Org_Culture	1			
Continuation	<---	Org_Performance	0.936	0.105	8.881	***
DM5	<---	Data_Mngt	1.106	0.126	8.799	***
DM4	<---	Data_Mngt	1.059	0.12	8.813	***
DM3	<---	Data_Mngt	1			
INV4	<---	Involvement	1			
INV3	<---	Involvement	1.006	0.115	8.764	***
INV1	<---	Involvement	0.838	0.108	7.743	***
ADP4	<---	Adaptability	1			
ADP3	<---	Adaptability	0.79	0.093	8.535	***
ADP2	<---	Adaptability	0.996	0.107	9.313	***
MIS3	<---	Mission	1.133	0.137	8.256	***
MIS1	<---	Mission	1			
DOC1	<---	Digital_Org_Culture	1			
DOC2	<---	Digital_Org_Culture	1.058	0.131	8.076	***
DOC3	<---	Digital_Org_Culture	1.127	0.133	8.495	***
DOC4	<---	Digital_Org_Culture	1.161	0.143	8.097	***
ITCU1	<---	Continuation	1			
ITCU2	<---	Continuation	0.967	0.062	15.536	***
OP2	<---	Org_Performance	1			
OP3	<---	Org_Performance	0.821	0.089	9.225	***
OP5	<---	Org_Performance	0.79	0.093	8.5	***

OP7	<---	Org_Performance	0.924	0.095	9.766	***
AU1	<---	Actual_Usage	1			
AU2	<---	Actual_Usage	1.381	0.186	7.442	***
SQ2	<---	SysQuality	1			
SQ3	<---	SysQuality	1.204	0.16	7.507	***
SQ4	<---	SysQuality	1.28	0.171	7.478	***
SQ5	<---	SysQuality	0.989	0.142	6.955	***

Structural Model - Standardised Regression Weights: (Group number 1 - Default model)

			Estimate
SysQuality	**<---**	**Data_Mngt**	**0.232**
Digital_Org_Culture	**<---**	**Data_Mngt**	**0.167**
SysQuality	**<---**	**Org_Culture**	**0.256**
Digital_Org_Culture	**<---**	**Org_Culture**	**0.693**
Actual_Usage	**<---**	**SysQuality**	**0.221**
Actual_Usage	**<---**	**Digital_Org_Culture**	**0.33**
Org_Performance	**<---**	**Actual_Usage**	**0.214**
Continuation	**<---**	**Org_Performance**	**0.727**
Involvement	**<---**	**Org_Culture**	**0.873**
Adaptability	**<---**	**Org_Culture**	**0.888**
Mission	**<---**	**Org_Culture**	**0.918**
DM5	<---	Data_Mngt	0.745
DM4	<---	Data_Mngt	0.748
DM3	<---	Data_Mngt	0.71
INV4	<---	Involvement	0.694
INV3	<---	Involvement	0.728
INV1	<---	Involvement	0.619
ADP4	<---	Adaptability	0.742
ADP3	<---	Adaptability	0.645
ADP2	<---	Adaptability	0.713
MIS3	<---	Mission	0.72
MIS1	<---	Mission	0.669
DOC1	<---	Digital_Org_Culture	0.657
DOC2	<---	Digital_Org_Culture	0.667
DOC3	<---	Digital_Org_Culture	0.715
DOC4	<---	Digital_Org_Culture	0.669
ITCU1	<---	Continuation	0.921
ITCU2	<---	Continuation	0.908
OP2	<---	Org_Performance	0.729
OP3	<---	Org_Performance	0.697

OP5	<---	Org_Performance	0.637
OP7	<---	Org_Performance	0.746
AU1	<---	Actual_Usage	0.811
AU2	<---	Actual_Usage	0.884
SQ2	<---	SysQuality	0.594
SQ3	<---	SysQuality	0.735
SQ4	<---	SysQuality	0.728
SQ5	<---	SysQuality	0.638

Structural Model - Variances: (Group number 1 - Default model)

	Estimate	**S.E.**	**C.R.**	**P**
Data_Mngt	0.408	0.076	5.367	***
Org_Culture	0.205	0.045	4.579	***
e66	0.165	0.039	4.23	***
e70	0.08	0.02	3.899	***
e69	0.337	0.062	5.453	***
e68	0.395	0.069	5.748	***
e62	0.073	0.027	2.671	0.008
e64	0.038	0.025	1.521	0.128
e65	0.075	0.029	2.566	0.01
e67	0.323	0.051	6.352	***
e9	0.4	0.058	6.925	***
e10	0.359	0.052	6.856	***
e11	0.401	0.053	7.617	***
e14	0.332	0.041	8.064	***
e15	0.277	0.037	7.505	***
e17	0.349	0.039	8.916	***
e22	0.29	0.039	7.528	***
e23	0.311	0.035	8.829	***

e24	0.341	0.043	8.021	***
e27	0.291	0.042	6.96	***
e29	0.301	0.038	7.999	***
e30	0.276	0.032	8.756	***
e31	0.293	0.034	8.659	***
e32	0.255	0.032	8.078	***
e33	0.349	0.04	8.635	***
e37	0.122	0.037	3.345	***
e38	0.136	0.035	3.897	***
e41	0.365	0.045	8.064	***
e42	0.296	0.035	8.488	***
e44	0.379	0.042	9.063	***
e46	0.283	0.036	7.806	***
e47	0.22	0.056	3.922	***
e48	0.226	0.101	2.23	0.026
e57	0.367	0.041	8.965	***
e58	0.247	0.035	7.072	***
e59	0.291	0.04	7.208	***
e60	0.286	0.033	8.545	***

Structural Model - Squared Multiple Correlations: (Group number 1 - Default model)

	Estimate
SysQuality	0.178
Digital_Org_Culture	0.621
Actual_Usage	0.204
Org_Performance	0.046
Continuation	0.529
Mission	0.843
Adaptability	0.788
Involvement	0.762
SQ5	0.407
SQ4	0.53
SQ3	0.54
SQ2	0.353
AU2	0.781
AU1	0.658
OP7	0.556
OP5	0.406
OP3	0.485
OP2	0.531
ITCU2	0.825
ITCU1	0.849
DOC4	0.448
DOC3	0.511
DOC2	0.445
DOC1	0.432
MIS1	0.447
MIS3	0.518
ADP2	0.508
ADP3	0.416
ADP4	0.55
INV1	0.383
INV3	0.529
INV4	0.481
DM3	0.504
DM4	0.56
DM5	0.555