Critical Success Factors for Implementing Artificial Intelligence (AI) Projects in Dubai Government United Arab Emirates (UAE) Health Sector: Applying the Extended Technology Acceptance Model (TAM)

العوامل المؤثرة الناجحة في تطبيق مشاريع الذكاء الاصطناعي في حكومة دبي دولة الإمارات العربية المتحدة في المجال الصحي: تطبيق النموذج الموسع لتقبل التكنولوجيا

by

SHAIKHA ALI MOHSIN ALATTAR ALHASHMI

Dissertation submitted in fulfilment

of the requirements for the degree of

MSc INFORMATICS

at

The British University in Dubai

March 2019

DECLARATION

I warrant that the content of this research is the direct result of my own work and that any use made in it of published or unpublished copyright material falls within the limits permitted by international copyright conventions.

I understand that a copy of my research will be deposited in the University Library for permanent retention.

I hereby agree that the material mentioned above for which I am author and copyright holder may be copied and distributed by The British University in Dubai for the purposes of research, private study or education and that The British University in Dubai may recover from purchasers the costs incurred in such copying and distribution, where appropriate.

I understand that The British University in Dubai may make a digital copy available in the institutional repository.

I understand that I may apply to the University to retain the right to withhold or to restrict access to my thesis for a period which shall not normally exceed four calendar years from the congregation at which the degree is conferred, the length of the period to be specified in the application, together with the precise reasons for making that application.

Signature

Shaikha FS

COPYRIGHT AND INFORMATION TO USERS

Abstract

Recently, the government of United Arab of Emirates (UAE) is focusing on Artificial Intelligence (AI) strategy for future projects that will serve various sectors. Health care sector is one of the significant sectors they are focusing on and the planned (AI) projects of it is aiming to minimize chronic and early prediction of dangerous diseases affecting human beings. Nevertheless, project success depends on the adoption and acceptance by the physicians, nurses, decision makers and patients. The main purpose of this dissertation is to explore out the critical success factors assist in implementing artificial intelligence projects in the health sector. Besides, the founded gap for this topic was explored as there is no enough sharing of multiple success factors that assist in implementing artificial intelligence projects in the health sector precisely. First of all, this dissertation analyze the mostly used external factors of the Technology Acceptance Model (TAM), by highlighting studies that address these factors, mainly Perceived Ease of Use, Perceived Usefulness, Attitude towards use and Behavioral intention to use. In order, to identify the most widely used factors a systematic review approach was conducted for 23 related research studies between 2015 and 2018 having quantitative and qualitative data. Second, a modified proposed model for this research was developed by using the extended TAM model and the most widely used factors. Third, to fit the purpose of this research a validation to the new model was used by the partial least squares-structural equation modelling (PLS-SEM). Data of this study was collected through survey from employees working in the health and IT sectors in UAE and total number of participants is 53 employees. The outcome of this questionnaire illustrated that managerial, organizational, operational and IT infrastructure factors have a positive impact on (AI) projects perceived ease of use and perceived usefulness.

Keywords: United Arab Emirates; Critical Success Factor (CSF), Technology Acceptance Model (TAM); Artificial Intelligence (AI), Health sector project, Managerial Factors, Operational, Strategic, IT Infrastructure, Organizational Factors and Structure Equation Modeling (PLS-SEM).

ملخص

في الآونة الأخيرة، تركز حكومة دولة الإمارات العربية المتحدة على استراتيجية الذكاء الاصطناعي التي تعتمد على المشاريع المستقبلية تخدم فيها مختلف القطاعات. من بين القطاعات الهامة التي تستهدفها هي مجال الرعاية الصحية، تهدف المشاريع المرتبطة بهذا القطاع إلى الحد من التنبؤات المزمنة والمبكرة بالأمراض الخطيرة التي تؤثر على البشر. ومع ذلك، يعتمد نجاح المشروع على الاعتماد والقبول من قبل الأطباء والممرضين واصحاب القرار والمرضى. الهدف الرئيسي من هذه الدراسة هو استكشاف عوامل النجاح التي تساعد في تنفيذ مشاريع الذكاء الاصطناعي في القطاع الصحي، حيث تم العثور على فجوة في عدم وجود دراسات كافية تشارك فيها عوامل نجاح في تنفيذ مشاريع الذكاء الاصطناعي في القطاع الصحي على وجه التحديد. لذا، أولا، يحلل البحث العوامل الخارجية المستخدمة في الغالب لنموذج قبول التكنولوجيا من خلال تسليط الضوء على الدراسات التي تتناول هذه العوامل، وأساسًا إدراك سهولة الاستخدام، ومدى إدراكه، واتجاهه نحو الاستخدام والنية السلوكية للاستخدام. من أجل تحديد أكثر العوامل استخدامًا على نطاق واسع، تم إجراء مراجعة منهجية لـ 23 دراسة بحثية ذات صلة بين عامي 2015 و2018 تحتوي على بيانات كمية ونوعية. ثانياً، تم تطوير نموذج مقترح معدّل لهذا البحث باستخدام نموذج قبول التكنولوجيا الموسع والعوامل الأكثر استخداماً. ثالثًا، من أجل ملائمة الغرض من هذا البحث، تم استخدام التحقق من صحة النموذج الجديد بواسطة النمذجة الجزئية الصغرى للمعادلات الهيكلية(PLS-SEM)

تم جمع بيانات هذه الدراسة من خلال استقصاء من العاملين في قطاعي الصحة وتكنولوجيا المعلومات في الإمارات العربية المتحدة وبلغ عدد المشاركين فيه 53 موظفاً. أوضحت نتائج هذا الاستبيان أن العوامل الهيكلية الإدارية والتنظيمية والتشغيلية وتقنية المعلومات لها تأثير إيجابي على مشاريع الذكاء الاصطناعي التي تعبر سهولة في الاستخدام و فائدة مدركة.

Dedication

This dedication goes to my **parents** and **late father** and my sister Miss, **Noora** and my greatest person in my life my husband **Faisal Al Amri** and my baby **Abdullah**.

Acknowledgment

With the name of Allah, I begin, I'm very thankful to Allah for doing this dissertation completion within the deadline. I really would like to thank the Telecommunications Regulatory Authority (TRA) for sponsoring my Masters' study and their continued support.

Also, I would like to thank Mr, Said Salloum for his continues support for doing this dissertation and guiding me in each step. I really appreciate my work collogue and lovely friend Miss, Nawal Harib AlMuhairi for her support, sharing valuable information towards completion of this paper. An appreciation to my teacher, Professor. Sherief Abdallah for teaching me research methods and applications. Also, Mr, Rawy Abdelrahman Thabet, Academic Associate for assisting and guiding me during my dissertation. I'm thankful for each person who did support me in doing this dissertation wither a direct or indirect way and special thanks and deepest feelings of gratitude goes to my husband Mr, Faisal Al Amri. Thank You all and GOD bless.

Table of Contents

List of Tables

List of Figures

List of Abbreviations

Artificial Intelligence	AI
Attitude Towards Use	ATU
Actual System Use	ASU
Business Intelligence	BI
Behavioral Intention To Use	BITU
Critical Success Factor	CSF
Customer Relationship Management	CRM
Data Management Information Systems	DMIS
Enterprise Resource Planning	ERP
Information Technology	IT
Perceived Ease Of Use	PEOU
Perceived Usefulness	PU
Technology Acceptance Model	TAM
United Arab Emirates	UAE
Extended Technology Acceptance Model	ETAM
Theory Of Reasoned Action	TRA
Diffusion Of Innovation Theory	DOI
Uniform Theory Of Acceptance And Use Technology	UTAUT
Theory Of Planned Behavior	TPB
Social Cognitive Theory	SCT
Dubai Health Authority	DHA
Computer-Aided Diagnosis	CAD
Information Technology	IT
Structural Equation Model	SEM

Chapter One

Introduction

1.1 Overview

The advancement in artificial intelligence technologies has employed software and system developers to come up with new techniques in improving medical care for patients. The term of artificial intelligence (AI) is a part of advanced technology trends and some of the intelligent tools were used to assist doctors and medical practitioners in making decisions for their patients based on their health conditions and history. Besides, other intelligence systems practices in predicting individual health issues by employing human being knowledge and emulate it into advanced technology. Furthermore, valueStrat (2018) illustrated a clear initiatives toward artificial intelligence implementation strategy by 2021 that is pushing gradually in the Gulf region, precisely Dubai government in United Arab Emirates (UAE), for the public sector (Government.ae 2018). Great example for Dubai Electricity and Water Authority (DEWA) partners with Dubai start up on (AI) innovative solutions for future labs to implement a pilot (AI) system for distribution system. Exploring out the necessity of government entities to take the initiatives seriously and start their artificial intelligence projects within their environments suiting their business requirements. Artificial Intelligence (AI) can be stated the simulation of different processes of human intelligence by machines, more so computer-related systems (Mokyr 2018). However, Swarup (2012) has a view that “Artificial intelligence (AI) state the intelligence of machines and the branch of computer science that aims to create it” (Swarup 2012). While giving its history, Mijwel (2015) refers to artificial intelligence as the idea that inanimate objects are made into intelligent beings that can reason like humans, some of human intelligence processes that are simulated by computer systems include learning, reasoning, problem solving, speech recognition and planning. The purpose of this dissertation is to bridge the gap for Dubai government health sector to continue improving artificial intelligence practice in providing services for patient monitoring (Dubai Health Authority 2018). It's justifiable that this dissertation will have its main focus on the critical success factors (CSF) for implementing artificial intelligence projects within the healthcare sector. It’s significant to provide the critical success factors that must be under consideration while developing artificial intelligence projects within the health care domain, by investigating theoretical existing literature studies in this dissertation.

Aim: Propose framework is the extended factors of the Technology Acceptance Model (TAM) and definitely it achieved this dissertation aim to define what are the critical success factors for implementing artificial intelligence projects for health care sector in Dubai?

Objective: Suggest to employ the basic Technology Acceptance Model (TAM) framework for achieving dissertation aim and the proposed model validation through the Structural Equation Model (SEM) described deeply in the methodology chapter.

1.2 Motivations

Artificial Intelligence technology is growing rapidly to become an effective contribution of monitoring patients and management control in the health domain. Advanced technology is serving various operations within the health industry such as, data management system, prediction of future diseases and examination patients health conditions. Employing artificial intelligence practices can affect people health conditions in the developed countries, supporting the society by predicting future illnesses and fighting against medication shortage. Moreover, UAE is having the insist and initiatives toward fostering the implementation of (AI) projects within their territory for quite some time. This is the researcher's motivation as for why the artificial intelligence concepts in the United Arab Emirates have not yet been fully integrated into various governmental domains such as healthcare (Government.ae 2018). Therefore, a need arises to analyze some of the factors that are considered to be critical and successful in implementing these projects. Analysis brought out for this dissertation to focus on examining previously published studies that utilized TAM as a theoretical framework to assist the proposed hypothesis in different fields and end with empirical examination of various external factors such as, managerial, organizational, operational, strategic and IT infrastructure factors on the acceptance and adoption of the artificial intelligence projects in healthcare (Fathema, Shannon & Ross 2015; Fayad & Paper 2015). Massive quantity of research studies relating to the critical success factors for Information Technology (IT) projects in various fields. However, it results that none of the literature review papers have explored all the following critical success factors in health domain such as, managerial, operational, strategic, IT infrastructure and organizational factors in one unique paper. Also, no single empirical research paper focused its potential on establishing (AI) projects in the healthcare sector within the United Arab Emirates (UAE). However, other research papers focuses on CSFs in IT projects for instance, Enterprise Resource Planning (ERP), Business Intelligence (BI) and Data Management Information Systems (DMIS). Besides, educational field is not an exceptional, various projects such as, e-learning is employing artificial intelligence knowledge to foster the educational sector.

Nonetheless, the dissertation contribution will add knowledge to the existing literature and demonstrate artificial intelligence projects critical success factors. The extension of this dissertation will assist the health domain in UAE and Dubai preciously in achieving some of their artificial intelligence strategies in the health area with consideration of the most successful factors that influencing and affecting the target aim in their domain (Government.ae 2018). Dubai government is on the move of becoming fully smart city, artificial intelligence in healthcare and other strategic sectors is one of the digital pillars that are under plan of being integrated toward the realization of the vision (Dubai Health Authority 2018). UAE does not have significant statistics concerning the state of AI in healthcare. Thus any empirical study that focuses on the utilization of the AI projects in the healthcare sector within UAE will be vital in the government's plans of smart city ideology. Furthermore, this dissertation describes extensively the CSF of (AI) projects in health sector and the structure way to understand these factors and prove its significance in enhancing the health care domain in Dubai government. Possibilities in monitoring patient's conditions will be manageable with effectiveness since the adoption and acceptance of (AI) projects will expand towards assisting individual's health history. Acceptance and adoption of (AI) projects critical success factors are dependable on the way it's operating and the provided advantages in the respective domain within healthcare. Referring to Who (2011), (AI) served in different roles within various sectors globally and these roles have been investigated by other authors for different studies according to their disciplines. According to (Aldosari et al. 2018), stated that nurses in hospitals are making diagnoses and noting down doctor's orders and playing an important role in adopting Electronic Medical Record in their environment. Nurses attitudes toward accepting or rejecting (AI) projects in their environment are important to adopt the defined (AI) project. Along as, there is no even a single previous study that addressed the five factors (managerial, operational, strategic, IT infrastructure and organizational) for implementing (AI) projects in the healthcare sector. Current dissertation evaluates these factors practices as far as adoption or rather acceptance of the (AI) projects in healthcare are concerned (Amer 2016). The major rationale behind this dissertation motivation is to conduct it focusing on Dubai Emirate that is one of the vital cities in Gulf region, initiating different (AI) strategies in the healthcare sector (Dubai Health Authority 2018).

1.3 Problem Definition

Multiple research studies illustrate that (AI) concepts have been employed in various projects within different domains such as, education, business and (IT). Dubai government started pushing organization in having AI projects in their environment for serving people in a better and faster way. UAE strategy for 2020 is to drive the growth by using artificial intelligence applications for better government performances and implementing innovative productive environments. (Khaleej Times 2019). For instance, Bennani and Oumlil (2014) pointed out that the acceptance and adoption of (AI) projects in health sector is practically depended on doctor's and physician's perceptions. Beside, previous research papers didn't study extremely the five factors managerial, operational, strategic, IT infrastructure and organizational together in single research paper, the influences of physicians believe for artificial intelligence projects execution in Dubai health sector. Bennani and Oumlil (2014) resulted three significant factors for acceptance of ICT projects in health domain, compatibility, Perceived Usefulness and Perceived Ease of Use.

Therefore, current dissertation analyzes the external factors of TAM, employed extensively for acceptance of (AI) concepts in projects (Nadri et al. 2018). Furthermore, an evaluation is conducted for the most widely used external factors considered to have an influence on (AI) projects, managerial, operational, strategic, IT infrastructure and organizational factors. Online questionnaire respondents were categorized to both employees from IT and health sectors picked from different government, semi-government and private organizations across the health sector in Dubai.

1.4 Aim of Research

Existing dissertation purpose is to explore out the five Critical Success Factors (managerial, operational, strategic, IT infrastructure and organizational) for implementing (AI) projects within the healthcare environment in Dubai, based on TAM model. Therefore, the main contribution of this dissertation to bridge the existing gap of not studying the above five factors within artificial intelligence projects for health care sector and it will be covered by investigate, explore and propose critical success factors within health sector and the relation between these CSF with artificial intelligence projects.

1.5 Research Questions

The aims and objectives of this study can be achieved by answering the following two questions:

a. What are the Critical Success Factors for Implementing Artificial Intelligence Projects for Health care sector in Dubai using the Technology Acceptance Model?
b. What are the common external factors with respect of (TAM) for Artificial Intelligence Health projects?

1.6 Methodology

Dissertation methodology is a mixed research method involves both exploratory and empirical research types. Primary data were obtained based on the mixed methodology as secondary information to support the primary findings was obtained from the existing literature of the previously published studies. Particularly, a survey design was used to get the quantitative primary data.

Data collection method in the current dissertation involves a carry out an assessment for the existing artificial intelligence projects in the healthcare division and primary data was employed to cover the existing gap. Precisely, meta-analysis design covered 23 published studies on the adoption and acceptance of (AI) and IT projects in the healthcare sector and other various fields like business, education, and IT. After conducting a systemic review of the credible sources, relevant hypotheses to this dissertation were formulated to understand what is expected in the field.

Online questionnaire survey utilized in this particular research study focused on employees working in IT and health sector in UAE. The quantitative data collection employed the use of a questionnaire survey that was filled online by the 53 respondents. Moreover, the Structural Equation Model (SEM) was used to carry out the evaluation of the measurement model that resulted in the emergence of the final path model. SmartPLS version 3.3.7 employed for this dissertation and the final model was tested using the good fit values.

1.7 Dissertation Outline

Presented dissertation is segmented into various categories and subcategories highlighting the significant components, the structure of the dissertation is as follows:

Chapter One: First chapter is the introduction section that presents an overview of the dissertation study, identifying research problem, motivations, aim and objectives that illustrates the significance of this dissertation. Finally, it is the methodology section that describes various aspects of data collection methods concerning the current dissertation.

Chapter Two: literature review, that studies the current situation of (AI) projects implementation process in the healthcare sector. Major emphasis was put on the implementation of the (AI) projects alongside other technological resources in the medical domain. Besides, this chapter explained various factors that are believed to influence the perceptions and concerning the use of (AI) in the health centers. Besides, the chapter concluded by reviewing TAM to link it with artificial intelligence projects in the healthcare sector.

Chapter Three: research model and hypothesis, it represents the employed research model for evaluation purposes for the widely used external factors of TAM. Different hypothesis listed down, along with the factors and a brief discussion concerning the elements of the theoretical model.

Chapter Four: Methodology assist in gathering the required sample data from the sample population in order to answer the research question for this dissertation, along with the utilized research structure and design.

Chapter Five: discussion of the founded results from the online questionnaire and the employed analysis techniques.

Chapter Six: conclusions, recommendations, and limitations of the existing dissertation are presented along with the future research recommendations.

Chapter Two

Literature Review

2.1 Overview

Present dissertation employed specialized methodology to assess the most employed external factors of the Technology Acceptance Model (TAM), considering the implementation of artificial intelligence projects in the health care sector. The systematic review and analysis of the previous studies only had an affinity with the previous studies that were published within the last three years, between 2015 and 2018. However, this dissertation explored a gap in the existing literature studies as none of the 23 sources did address the external factors for extending the Technology Acceptance Model in implementing Artificial Intelligence projects within the health sector. Therefore, this dissertation is considered relevant as the topic has never been explored before using the five factors managerial, operational, organizational, strategic and IT infrastructure.

However, to find relevant studies in relation to the research topic, studies from different fields such as Information Technology, education, and business considered appropriate and incorporated. Basing on the literature study findings, the TAM's external factors that are used extensively include but not limited to: system quality, computer playfulness, self-efficacy, content quality, subjective norm, accessibility, enjoyment, and information quality (Abdullah & Ward 2016; San & Yee 2013; Strudwick 2015). Also, studies have examined the way these most widely employed external factors influence the five main constructs of the Technology Acceptance Model in relation to the types of artificial intelligence and the user types of it. The integration of the Extended

Technology Acceptance Model was based on several external factors mentioned above. Basing on ETAM constructs, the above factors will be significant in implementing artificial intelligence projects in the healthcare sector (Phatthana & Mat 2011). Moreover, the data obtained is believed to be authentic since the published studies in different fields with TAM's statistical meta-analysis were called upon for review. Basing on the research findings from previously published studies, the Technology Acceptance Model (TAM) is not only a valid model but also a robust with extensive use as it is applicable in numerous fields within a very wide context (Alharbi & Drew 2014). Furthermore, a moderator analysis of both user and usage types was conducted during the assessment of the situations that could result in the exhibition of distinct outcomes laid out by the Technology Acceptance Model. A closer look at the provisions of the model and the way Bennani and Oumlil (2014) explained that health professionals play an important role while implementing artificial intelligence projects in their area.

2.2 Introduction

Artificial Intelligence is a branch of computer science that simulates human processes into computer systems (Swarup 2012; Kok et al. 2009). means that computer systems are made to behave and act like human beings. “Nowadays, more and more computer technology and artificial intelligence take part in disease diagnosis” (Zhao et al. 2017) but “our possible relations to AI persons could be more complicated than they first might appear” (Lawrence et al 2016). It means that advancing technology is impacting human life directly in such a way that almost all aspect of the people is bound to the impacts of the technologies. However, the way people relate with the computer systems can be said to be much more complicated than it is literally assumed in the public domain. Nonetheless, service delivery in the current health care sector is prone to succumb to the effects of digital disturbance as information technologies and internet influence the way physicians carry out their daily professional tasks while attending to their clients. For example, Moen et al. (2016) assert that the process of managing information is time-consuming for healthcare providers and implementation of relevant projects such as electronic health record systems allow clinicians to document the patient care records without much difficulty and again, free.

According to Ziuziański et al. (2014), implementation of artificial intelligence projects in health care results in improving the sector. Specifically, AI has proved to be significant in different healthcare practices such as a neural network, data mining, deep learning and machine learning (Jordan & Mitchell, 2015). Referring to artificial intelligence it's considered a technology on itself and this technology has been known for making the work of different personnel not only easier but also manageable within short time. While implementing Artificial Intelligence projects in the health domain, some enhancement opportunities could be resulted from the process of having accurate patients 'data and translate it to a clear useful information.

It is due to such benefits that artificial intelligence projects are gaining much popularity in the health care sector. Wallis et al. (2017) state that in spite of the fact that benefits of implementing artificial intelligence projects in healthcare have received much acknowledgment in the medical domain, there are some instances in which these implementations fail because of the rejections fostered by stakeholders in the field. Besides, the practice of rejection has prompted creation and testing different technology adoption models to give a clear prediction of the sources of rejections that some of the artificial intelligence projects get during their implementation stages (Najafabadi et al., 2015). Some of these technology adoption models are Theory of Reasoned Action (TRA), Diffusion of Innovation Theory (DOI), Technology Acceptance Model (TAM), Uniform Theory of Acceptance and Use of Technology (UTAUT), Theory of Planned Behavior (TPB), and Social Cognitive Theory (SCT) (Maruping et al., 2017). Among the listed technology adoption theories, technology acceptance model that has extensively been employed in the information system to determine the acceptance of the technology among desired users.

The main reason for conducting this particular research study is that there is a big gap existing in the current literature between the implementation of artificial intelligence projects in health care and the acceptance of those projects by the users. The existing literature only focuses on the acceptance of the technology projects in general but it does not narrow down to artificial intelligence projects in the health domain exactly. Therefore, the main research question that this study is based on is: What are the Critical Success Factors for Implementing Artificial Intelligence Projects for Health care sector in Dubai using the Technology Acceptance Model?

Unlike other typical Information Technology projects, artificial intelligence project deals with simulation of the human processes by machines (Mokyr 2018; Mijwel 2015), hence their uniqueness. On the other hand, implementation of the AI projects in healthcare within the Gulf region also comes with its own uniqueness. Specifically, Gulf region is now zooming out on having smart cities that create a necessity of implementation of the current technologies such as AI in most of the sectors.

2.3 Artificial intelligence projects in the health sector

The concept of Artificial Intelligence in the health domain is bound to the probabilities patient's health improvements and cost reduction in the health care sector. Different organizations in the health industry are integrating the provisions of machine learning as they make both better and faster diagnoses comparing to human beings. Having a closer look at the current strategy of artificial intelligence being adopted in (UAE), it illustrates that this strategy aims for making the country to be the first in the world as far as artificial intelligence investments are concerned.

Precisely, Vistdubai.com (2018) states that Dubai Health Authority (DHA) has already put in place a strategy which uses both artificial intelligence and robotics to make the processes of healthcare automatic with an aim of meeting the rising local and regional demands. The strategy has an objective of ensuring the success of the (DHA) mission that states, "Harnessing creativity and innovation by generating and transforming ideas into reality to deliver value-based and sustainable healthcare services through engaging all partners and stakeholders" (Dubai Health Authority 2018). Indeed, providing services through artificial intelligence as well as maximizing integration of the AI concepts into the medical services is one of the five themes laid out in the UAE AI strategy. Currently, there are numerous projects of Artificial Intelligence that have been implemented in healthcare to achieve the desired outcomes of improving patients' results as well as reducing the costs of healthcare. For instance, IBM Watson is a healthcare technology that has the ability to understand natural language (IBM 2018). Computer systems can also give responses to questions if prompted to do so and this system is therefore used to dig deep into the relevant data of the patient as well as other sources of data that are available.

According to Price (2017), the influence of Artificial Intelligence in the healthcare system is growing rapidly to bring changes in the sector. Precisely, medicine field is experiencing major developments in both big data and sophisticated machine learning techniques (Price 2017). As far as Kononenko (2001) is concerned, one of such developments is the way machine learning is being used currently to give different indispensable tools that are necessary for analyzing medical data intelligently. It is, therefore, true that Artificial Intelligence is playing significant roles in the healthcare sector by giving solutions to biomedical problems (Shukla, Lakhmani & Agarwal 2016).

According to Albu and Stanciu (2015), one of the domains where predictions are appreciated with the importance they deserve is medicine. Artificial intelligence systems have excellency in conducting predictive analytics. According to Panicacci et al. 2018), machine learning algorithms predict the hospitalization risks as well as death chances based on either socio-economic or predictive data. It is even stated that "Predictive analytics for healthcare using machine learning is a challenging task to help doctors decide the exact treatments for saving lives" (Charleonnan et al. 2016).

In the literature research conducted by Nithya and Ilango (2017), it was found out that machine learning is effective when predictive analytics involves a huge data set. But again, Rajamhoana et al (2018) link both prediction and treatment of the diseases such as heart attack to the extraction of medical data. In such circumstances, effective predictions and management of conditions call for daily monitoring (Zhang, Zhou & Zeng 2017). Basing on Yamada and Kobayashi (2018), health monitoring improves the quality of life as well giving required support for aging populations

(IEEE Xplore Digital Library 2016). Moreover, AI projects in healthcare help in censoring data which is helpful in the prognosis modeling of the diseases (Chen et al. 2018). Also, AI projects make it possible for the enhancement of the Computer-aided diagnosis (CAD) systems which improves the computed tomography's feasibility as explained by Nibali et al. (2017). For instance, Fotin et al. (2016) point out that the use of CAD has been active in the screening mammography for a long period. Mammography screening increases the rate of detecting breast cancer during the early stages of the condition's development (Ertosun & Rubin 2015). From this discourse, it is shows that implementing Artificial Intelligence projects results in the development of beneficial systems in the healthcare sector, ranging from making physicians work with a sense of simplicity and with a lot of ease of saving valuable resources such as time and energy (Albu & Stanciu 2015; Shaikhina & Khovanova 2017). According to Vemulapalli et al. (2016), the methods of the advanced artificial intelligence within the healthcare sector have capabilities of bringing about the highest quality of care in three different ways. Ensuring that non-obvious is discovered, enhancing relationships relevant in the clinical settings and ensuring that timely are interventions are enabled.

The main reason for conducting this particular research study is that there is a big gap existing in the current literature between the implementation of artificial intelligence projects in health care and the acceptance of those projects by the users. The existing literature only focuses on the critical success factors that allow to accept artificial intelligence projects in general but does not narrow down to artificial intelligence projects in the medical domain. Therefore, the main research question that this study is based on is: what are the critical success factors for implementing artificial intelligence projects in the healthcare sector in Dubai? Unlike other typical Information Technology projects, artificial intelligence projects deal with simulation of the human processes by machines, hence their uniqueness. On the other hand, implementation of the AI projects in healthcare within the Gulf region also comes with its own uniqueness. Specifically, Gulf region is now throwing up smart cities that create a necessity of implementation of the current technologies such as AI in all sectors.

2.4 The Technology Acceptance Model (TAM)

Recognitions of various technologies in different sectors, TAM has established itself as a strong component in facilitating the acceptance of these technologies. Based on the studies reviewed, system quality, computer self-efficacy, self-efficacy, satisfaction, subjective norm, trust, enjoyment and information quality are the most common external factors that are widely used (Baharom, Bashayreh, Khorma & Mohd 2011; Fayad, R. & Paper 2015). Indeed, TAM is now a vital framework that is employed in different sectors to integrate the ever-advancing technology.

For instance, Amer (2016) used TAM when coming up with various factors that impact the adoption as well as the implementation of Business Intelligence and Analytics Projects in Organizations. The Technology Acceptance Model is built on two distinct but related personal beliefs, perceived usefulness as well as perceived ease of use (Marangunić & Granic 2015).

However, the two identified pillars of the TAM are known to be influenced by not only external but also system-specific factors called upon while the process of making predictions of the subject's attitude towards accepting and integrating the respective technology desired.

It is also a common notion in the public domain that as much as the attitude of the technology users is influenced by the system-specific and external factors, the attitude itself influences the behavioral intention of the technology users to adopt and implement the proposed technology in all the sectors. It is this fact that forms the ground for justifying the way system use is predicted in the actual settings. According to Briz-Ponce and García-Peñalvo (2015), the main objective of the establishment of the Technology Acceptance Model is to assist in determining readiness of users in accepting the information systems. The figure below shows the original TAM by (Davis 1989).

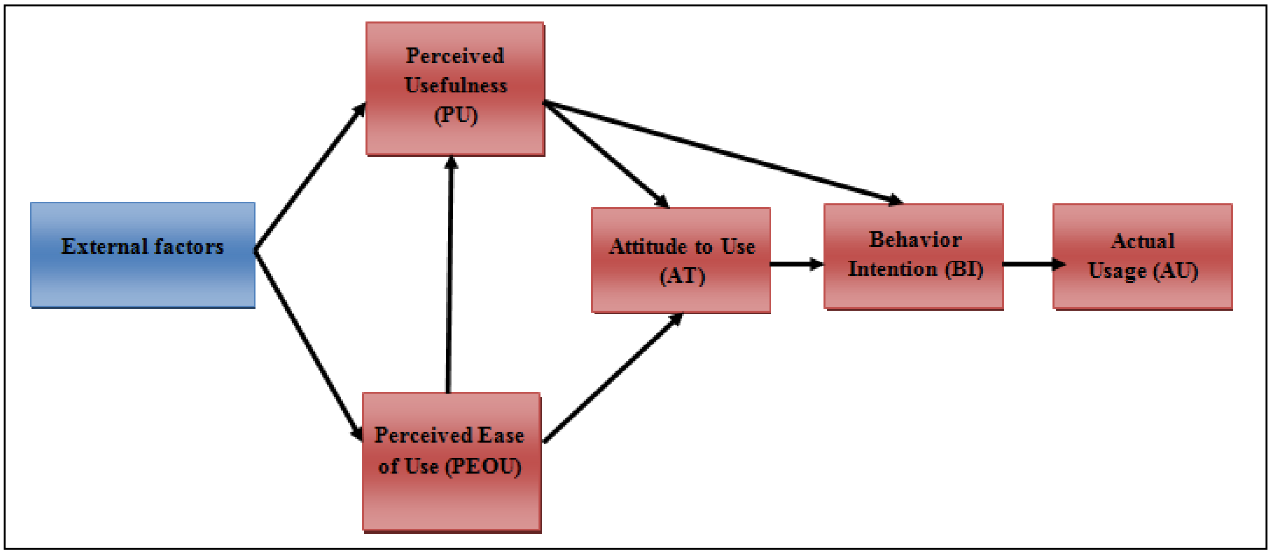

Figure 1. Original Technology Acceptance Model (TAM) by (Davis 1989)

A closer look at the TAM shows that various determinant factors influencing both computer use and other related or rather pertinent technologies in different contexts are explicitly explored by the model (Muk & Chung 2015; Teeroovengadum, Heeraman & Jugurnath 2017). Specifically, the TAM provides a good platform of the description of technology acceptance influencers in distinct user groups and technologies (Nadri, Rahimi, Afshar, Samadbeik & Garavand 2018; Solano-Lorente, Martínez-Caro & Cegarra-Navarro 2013). In general, its' clear that TAM has a single purpose, is to investigate the way external factors lead to influencing attitudes, intentions as well as beliefs through recognition of the few variables that brought out in previous studies.

However, Emad, El-Bakry and Asem (2016) assert that the process is done with consideration of not only cognitive but also emotional factors that dictate technology acceptance among user groups.

2.5 Linking Technology Acceptance Model (TAM) to Artificial Intelligence projects

There are different themes in the existing literature capable of assessing how different user groups accept the implementation of artificial intelligence projects in the health care sector. Since the Technology Acceptance Model has been effective in giving out the rationale for people accepting the technologies, it is considered to be a significant predictive framework in the medicine domain (Alloghani, Hussain, Al-Jumeily & Abuelma'atti 2015; Emad et al. 2016; Fathema, Shannon & Ross 2015). Despite the fact of TAM's origin is linked to the United States of America, the provisions and concepts of this robust predictive model has had a rapid widespread and it is now being employed in different parts of the globe within different contexts (Basak, Gumussoy and Calisir, 2015; Safdari, Saeedi, Valinejadi, Bouraghi, and Shahnavazi, 2017; Punnoose, 2012). According to Emad et al. (2016), external factors are considered to be extensively exhausted while extending the concepts of TAM to various corners of the world in the health care sector. After carrying out a systematic analysis of 23 studies published in the duration of four years (2015-2018), a total of 56 external factors were identified and assessed. Only five out of the 56 external factors were considered to be widely used in fostering technology acceptance among the user groups. include managerial, operational, organizational, strategic and IT infrastructure (Emad et al, 2016; Who, 2011; Wangpipatwong, Chutimaskul and Papasratorn, 2008).

After obtaining relevant published studies, different constructs presented in the research studies were put together to come up with a list of the external factors relied upon frequently during the process of adopting the technology. Also, factors that appeared in three or more studies were considered as the most widely used external factors in the whole idea of extending TAM during the technology acceptance process. The table below shows the distribution of various external factors obtained from different studies.

Authors	Technology type	Sample size	country	User type	TAM constructs					External factors				
					PEOU	PU	AT	I	U					
1. (Who, 2011)	Business	264		Customers	Y	Y		Y		Trust				
2. (Strudwick,2015)	Healthcare	20	Canada	Physicians	Y	Y				Safety Dimensions	Training	Social influence	Personality traits	Facilitating conditions
3. (Emad, El-Bakry and Asem, 2016)	Healthcare		Egypt	Physicians	Y	Y	Y	Y	Y	Subjective norms	Image	Job relevance		
4. (Helia, Asri, Kusrini, and Miranda, 2018)	Healthcare	200	Indonesia	Physicians	Y	Y	Y	Y	Y	Subjective norm	Satisfaction			
5. (Safdari, Saeedi, Valinejadi, Bouraghi, and Shahnavazi, 2017)	Healthcare	15	Iran	Physicians, nurses, and managers	Y	Y		Y		Computer self-efficacy	Social influence			
6. (Nadri, Rahimi, Afshar, Samadbeik, and Garavand, 2018)	Healthcare	202	Iran	Physicians	Y	Y				Image	Subjective norm	voluntariness	Job relevance	Output quality

7. (Fayad, R. and Paper, 2015)	e-Commerce	100	Lebanon	Customers	Y	Y	Y			Satisfactions,	Intentions	Expectations		
8. (San and Yee, 2013)	Healthcare	189	Malaysia	Physicians	Y	Y	Y			Education level	Social influence	Cost factor	Training	IT Vendor support
9. (Baharom, Khorma, Mohd and Bashayreh, 2011)	Healthcare	187	Malaysia	Doctors	Y	Y	Y	Y	Y	Individual capabilities	Technological factors	Behavioral perspectives		
10. (Teeroovengadum, Heeraman and Jugurnath, 2017)	Education	365	Mauritius	Teachers	Y	Y	Y			Computer self-efficacy	School climate	Individual self-efficacy		
11. (Bennani and Oumlil, 2014)	Healthcare	51	Morocco	Physicians	Y	Y				Compatibility				
12. (Bennani and Oumlil, 2014)	Healthcare	200	Morocco	Physicians	Y	Y	Y	Y	Y	Social norms	Trust			
13. (Alharbi & Drew, 2014)	e-learning	26	Saudi Arabia	Students	Y	Y	Y			lack of LMS availability	Experience	Job relevance		
14. (Solano-Lorente, Martínez-Caro, and Cegarra-Navarro, 2013)	Healthcare	256	Spain	Healthcare users	Y	Y			Y	Information quality	System quality	Satisfaction	loyalty	
15. (Phatthana and Mat, 2011)	Health tourism	236	Thailand	Physicians	Y	Y				Image				
16. (Punnoose, 2012)	e-learning	249	Thailand	Students	Y	Y				Computer self-efficacy	Extraversion	Neuroticism		

17. (Wangpipatwong, Chutimaskul, and Papasratorn, 2008)	e-Government	614	Thailand	Citizens	Y	Y				Computer self-efficacy				
18. (Basak, Gumussoy and Calisir, 2015)	Healthcare	339	Turkey	Physicians	Y	Y		Y		Perceived enjoyment	Subjective norms	Personal innovativeness	Computer self-efficacy	
19. (Basak, Gumussoy and Calisir, 2015)	Healthcare	339	Turkey	Physicians	Y	Y		Y		Perceived enjoyment	Subjective norms	Personal innovativeness	Computer self-efficacy	
20. (Amer 2016)	Business	100	UAE	Customers						Organizational	technological	Environmental		
21. (Salloum 2018)	Education		UAE	Students	Y	Y	Y	Y	Y	Computer efficacy	Social norms	Satisfaction		
22. (Alloghani, Hussain, Al-Jumeily and Abuelma'atti, 2015)	Healthcare	144	UAE	Physicians	Y	Y				Trust	Security			
23. (Fathema, Shannon and Ross, 2015)	Education	560	USA	Teachers	Y	Y		Y		Individual self-efficacy	System quality	Facilitations conditions		

Table 1. 23 Studies were reviewed to identify external factors of TAM

2.6 Summary

The science of simulating machines to perform different human processes is called Artificial Intelligence, including learning, reasoning and solving problems. With advancing technology, artificial intelligence is affecting almost every sector of human life, includes the healthcare sector that is an essential segment in the lives of human beings. Implementation of artificial intelligence projects in healthcare is beneficial in numerous ways. For instance, it provides a good platform on which the patient's data is managed. The resultant information can be employed in predictive analytics, which in turn influences the monitoring process of the patients' conditions. It is also noted that previous research studies failed to link the acceptance of artificial projects in healthcare by the user groups. created a literature gap that this study has an objective of bridging. Healthcare sector projects are much different from the other sector projects because they deal with delicate human life once implemented. Besides, literature review chapter has different aims and goals such as, reviewing systematically the most recent artificial intelligence projects adoption systems findings that have fostered the rapid extension of the Technology Acceptance Model and identifying the most widely used external factors. Additionally, this chapter has a goal of identifying various strengths of the precise relationship that might be in existence among these external factors that are widely used in promoting the variables of the Technology Acceptance Model in the implementation of artificial intelligence projects within the health sector. After reviewing 23 research studies it illustrated that system quality, computer self-efficacy, self-efficacy, satisfaction, subjective norm, trust, enjoyment and information quality are the most widely used external factors for promoting the Technology Acceptance Model. Finally, none of the 23 research papers did address the five factors together in one research paper (managerial, technological, operational, strategic and IT infrastructure.

Chapter Three

Research model and hypothesis

3.1 Overview

Findings of the literature research considered Technology Acceptance Model as a robust model have been discussed and used in numerous domains such as healthcare, education, business and others. After identifying (TAM) as a perfect role model for this existing research study, a moderator analysis was carried out in order to determine user types as well as the usage types of artificial intelligence. Furthermore, the importance of systematic review through meta-analysis approach was depicted vividly as both literature review and qualitative technique. It is through the help of the meta-analysis systematic review that different factors are believed to influence the acceptance or adoption of artificial intelligence projects within the healthcare sector. Also, the most widely used external factors that influences the implementation of artificial intelligence projects in various sectors are categorized into managerial, technological, operational, strategic and IT infrastructure. The main objective of this chapter is to build up a modified (TAM) model with the consideration of different hypotheses. Development of the Technology Acceptance Model, existence association between the most widely used external factors and the five basic constructs of Technology Acceptance Model is brought out.

3.2 Research framework and hypothesis

Proposed framework for the modified technology acceptance model in this chapter to assist in describing the existing research problem in the study and implement a research model.

3.2.1 Managerial Factors

According to Costantino et al. (2015), managerial factors refer to the influencers within the organization that impact on the various functioning aspects of the given organization such as adoption of the technology. Moreover, management role is to build up a trust and sets out organizational norms in the work environment. Trust element is important to be among employees in the health sector and it goes with mentality of the individual towards another person. It is considered as a way to illustrate individual's gratitude or faith of having a total belief on certain thing. When an individual trusts another person, the person has some assurances or rather certain degrees of certainty that one' assertion is reliable. In order to implement artificial intelligence projects in health sector, it's important to have the trust of physicians to help in offering necessary assistance to the project process. Precisely, data from the systemic review shows that perception on trust has a positive influence on the perceived usefulness as well as the perceived ease of use of artificial intelligence projects in the health sector. Besides, the subjective norm is actually assumed as a managerial factor to be one of the variables that influence the perceived social pressure to avoid a particular behavior. Social norm can be stated in this context as the perception of a person that the majority of people surrounding him or her think on what the individual must act according to the stated behavior. Scenarios of some individuals developing systems for others confirming their needs and requirements, hence dictating the ability of the subject individual to do or not do regarding the task in the question. For instance, people in the question fail to focus on their own emotional behavior as well as beliefs. Hence, there are two hypotheses that can be formulated as shown:

H1a: Managerial factor has a positive impact on perceived usefulness

H1b: Managerial factor has a positive impact on ease of use

3.2.2 Organizational Factors

Beginning with the organizational factor, it is considered as variables within a firm that allow individuals to either accept or reject any new technology in their environment. Organizations that support innovative and innovation technological projects, members are willing to accept any technological project (Baptista, G. & Oliveira 2015). Having fit in training programs in an organization, assist indivisual's to accept advanced technologies and enhance their skills (Navimipour & Soltani 2016).

According to Venkatesh, Thong, and Xu (2016), the availability of local expertise within the work environment increases the possibilities of accepting and adopting new technology by the target users. Moreover, the presence of global partnership with companies promotes the acceptability and adaptability of the new technology in organizations. From the findings, it can be said that the organizational factors not only have positive impacts on the perceived usefulness but also on the perceived ease of use of artificial intelligence projects within the healthcare sector. Therefore, the following hypotheses were formulated:

H2a: Organizational factor has a positive impact on perceived usefulness.

H2b: Organizational factor has a positive impact on ease of use

3.2.3 Operational Factors

Operational factor reflects the variables that are used to evaluate the choices with concern of the capability to achieve the requirements of desired service (Christensen et al. 2018). Perceived enjoyment can be described as the method of using a specified system that tends to perceive the action as enjoyable. An association between enjoyment and acceptance of new technology has been analyzed (Bennani & Oumlil 2014; Who 2011). Furthermore, enjoyment triggers positive impacts on the so-called intrinsic variables on the ways users perceive the technology being accepted. It is also a common assertion in the public domain that the amount of enjoyment one feels while intersecting with a new technology system can reduce the user's point of view on the effort required to use the very technology system being used (Who 2011). Also, perceived enjoyment is an important factor that uses to determine the acceptance or adoption of artificial intelligence projects in the healthcare sector. It is therefore understood that perceived enjoyment has a significant effect on the perceived usefulness of artificial intelligence projects in the health sector. Elsewhere, the systematic research conducted also presented in the literature section show that perceived enjoyment has a positive effect on the perceived ease of use of artificial intelligence projects in healthcare. From this finding, two hypotheses can be formulated as follows:

H3a: Operational factor has a positive impact on perceived usefulness.

H3b: Operational factor has a positive impact on ease of use

3.2.4 Strategic Factors

According to Zare (2017), strategic factors are the way that an organization has to get right for it to succeed with different stakeholders in order to reach the success of the industry. Users satisfaction in the health domain is the key strategy success while implementing (AI) projects. Satisfaction refers to the level of the person being pleasant with the current situation.

Satisfaction comes with the individual condition by having a relaxed emotional feeling that does not require from him or her to look for other options. For this scenario, perceived satisfaction can be illustrated as the level of which doctors and project leaders in healthcare get contented with the artificial intelligence projects. According to the previous researches, it was observed that perceived satisfaction is accompanied with the development of artificial intelligence projects in health sector. Precisely, the systemic review conducted shows that perceived satisfaction has an impact on the perceived usefulness of artificial intelligence projects in the healthcare sector. Also, it is highlighted in the data from the systemic review that perceived satisfaction has an impact on the perceived ease of use of artificial intelligence project within the healthcare sector. Therefore, the following two hypotheses can be formulated from this explanation:

H4a: Strategic factor has a positive impact on perceived usefulness.

H4b: Strategic factor has a positive impact on ease of use

3.2.5 The Information Technology (IT) infrastructure factor

described as the variables that dictate the physical systems such as hardware of the systems aspects within the organization (Dahiya & Mathew 2016). Three system factors are including in IT infrastructure system quality, content quality and information quality. Besides, system quality plays respectively in term of determining the way that feature of the systems include such as availability, usability, adaptability, and reliability of the given technology. For this case artificial intelligence, impact the overall look of the technology users as far as healthcare is concerned. Artificial intelligence impacts on the overall outlook of the technology users as far as healthcare sector is concerned. As per the systematic review, it was discovered that the system quality characteristics are important in accepting, adopting and then use artificial intelligence projects within medicine domain. Based on the previous reviewed studies, it was determined that system quality has a positive impact on the perceived use of artificial intelligence projects. Moreover, the systematic review under meta-analysis in literature research also revealed that system quality is believed to have a positive impact on the perceived usefulness of the artificial intelligence projects in the healthcare sector. According to Solano-Lorente, Martínez-Caro, and Cegarra-Navarro (2013), content quality shows the intense depth and regular developments of the content within artificial intelligence projects. Content quality described as one of the most important factors that defines the acceptance and adoption of artificial intelligence projects in the healthcare. Based on the systematic review results, it shows a positive relationship among content quality and perceived usefulness of artificial intelligence projects within the healthcare sector (Fathema, Shannon & Ross 2015; Solano-Lorente, Martínez-Caro & Cegarra-Navarro 2013). Moreover, content quality impacts positively on the perceived ease of use of artificial intelligence projects in the healthcare division. Information quality can be described to be the way that artificial intelligence projects in health domain can be used to get the proper information that can prove to be suitable in monitoring and management of patients (Basak, Gumussoy & Calisir 2015). Referring to the assertion presented by San and Yee (2013), information must be suitable for the time frame and easy to understand for comprehension in the patient treatment and health management conditions. Moreover, information quality can be used to refer to the belief of the users concerning the quality of the data or rather information presented by the various forms of artificial intelligence projects in the healthcare sector (Solano-Lorente, Martínez-Caro & Cegarra-Navarro 2013). Therefore, it is true to say that information quality is the level at which the physicians and patients receive precise and well-timed information based on the artificial intelligence frameworks in the healthcare domain. Based on previous reviewed researches, it was found that information quality has a vital impact on the perceived ease of use of the artificial intelligence projects in the healthcare sector (Safdari, Saeedi, Valinejadi, Bouraghi, & Shahnavazi 2017). Besides, the same systematic review revealed that the information quality significantly impacted on the perceived usefulness of (AI) projects in the healthcare sector. From these assertions, two hypotheses can be formulated concerning the impact of information quality on both perceived ease of use and perceived usefulness of the AI projects in medicine domain.

H5a: Infrastructure factor has a positive impact on perceived usefulness.

H5b: Infrastructure factor has a positive impact on ease of use

3.3 The constructs of Technology Acceptance Model

TAM model explains the general elements of acceptance that illustrates user's behavior, including two beliefs of Perceived Usefulness (PU) and Perceived Ease of Use (PEU).

3.3.1 Perceived ease of use (PEOU)

The perceived ease of use of any given system is defined as the level of technology used having the perception of proper use of the defined technology. Apart from the healthcare sector, there are numerous fields in which the implementation of the artificial intelligence topic has been studied (Alloghani, Hussain, Al-Jumeily & Abuelma'atti 2015; Phatthana & Mat 2011). There are numerous published studies in the existing literature showing that perceived ease of use has a significant relationship with the specific Behavioral Intention to Use either indirectly or in a direct way. Based on the implementation of the artificial intelligence projects in the health sector, perceived ease of use can be said to be the extent to which the physicians view using the artificial intelligence projects will not need a lot of efforts as the task will be easy as Phatthana and Mat (2011) explain. From the findings, a hypothesis can be formulated stating that:

H2a1: Perceived ease of use affects positively on the behavioral intention to implement artificial intelligence projects in the healthcare sector.

H2a2: Perceived ease of use affects positively on the perceived usefulness to implement artificial intelligence projects in the healthcare sector.

H2a3: Perceived ease of use affects positively on the attitude towards the implementation of artificial intelligence projects in the healthcare sector.

3.3.2 Perceived usefulness (PU)

According to Alharbi and Drew (2014), perceived usefulness refers to the level at which the users should expect the way using new technology promotes the performance of their jobs. In healthcare, artificial intelligence can be used to improve the performance of the physicians (Alloghani, Hussain, Al-Jumeily & Abuelma'atti 2015). However, artificial intelligence projects within healthcare will only be accepted or adopted if the physicians perceive that those projects will improve their performance at the job. Also, Previous studies confirmed that perceived usefulness has a significant relationship with attitude towards implementation of (AI) projects in the healthcare sector (Emad, El-Bakry & Asem 2016).

H2b1: Perceived usefulness affects positively on the attitude towards the implementation of artificial intelligence projects in the healthcare sector.

H2b2: Perceived use ease of use affects positively on the behavioral intention to implement artificial intelligence projects in the healthcare sector.

3.3.3 Attitude towards use (ATU)

Attitude refers to the degree to which people depict or rather portray their positive or negative feelings towards something. In this case, the attitude of the physicians will refer to the level in which they portray either positive or negative feelings towards the implementation of the artificial intelligence projects in the healthcare sector. Baharom, Khorma, Mohd, and Bashayreh (2011) explain that attitude has been significantly associated with behavioral intention. In addition, physicians' attitude affects the acceptance, adoption, and use of artificial intelligence projects in health care sectors. Therefore, the following hypothesis can be formulated:

H2c: Attitude towards use affects positively on the behavioral intention to implement artificial intelligence projects in the healthcare sector.

3.3.4 Behavioral intention (BI)

Physicians intention to implement (AI) projects in the healthcare sector can define the proposed or preferred behavioral intention to use in a particular context. Different studies have shown that behavioral intention to use has a direct and significant influence on the actual system use of implementing (AI) projects in the healthcare (Fayad & Paper 2015; Helia, Asri, Kusrini & Miranda 2018). With this, the following hypothesis can be formulated:

H2d: the behavioral intention to use effects positively on the actual system used to implement artificial intelligence projects in the healthcare sector.

3.3.5 Actual system use (ASU)

The actual system use refers to the precise period that the technology system is being utilized in its intended use after being accepted and adopted by the respective subject as captured by Teeroovengadum, Heeraman, and Jugurnath (2017). In this case, it means the time that (AI) concepts are put into practice after IT and health staff within heal sector implements the stated projects. However, this construct is dependent on other (TAM) constructs, particularly the behavioral intention to use.

H2e: the actual system use is affected positively by the behavioral intention to use to implement artificial intelligence projects in the healthcare sector.

3.4 Summary

Research model and hypothesis presented the modified Technology Acceptance Mode(TAM)l as well as implement various hypothesis concerning the constructs of the model under discussion. While developing the Technology Acceptance Model, the association that might be in existence between the external factors that are most widely used and the five basic constructs of Technology Acceptance Model is brought out. Factors such as managerial, organizational, operational, strategic and IT infrastructure are the most widely used external factors for promoting the Technology Acceptance Model that have been discussed in this chapter. Each factor was attached with its hypothesis and the ascertain of the validity and effectiveness of these hypothesis will be according to the explored results.

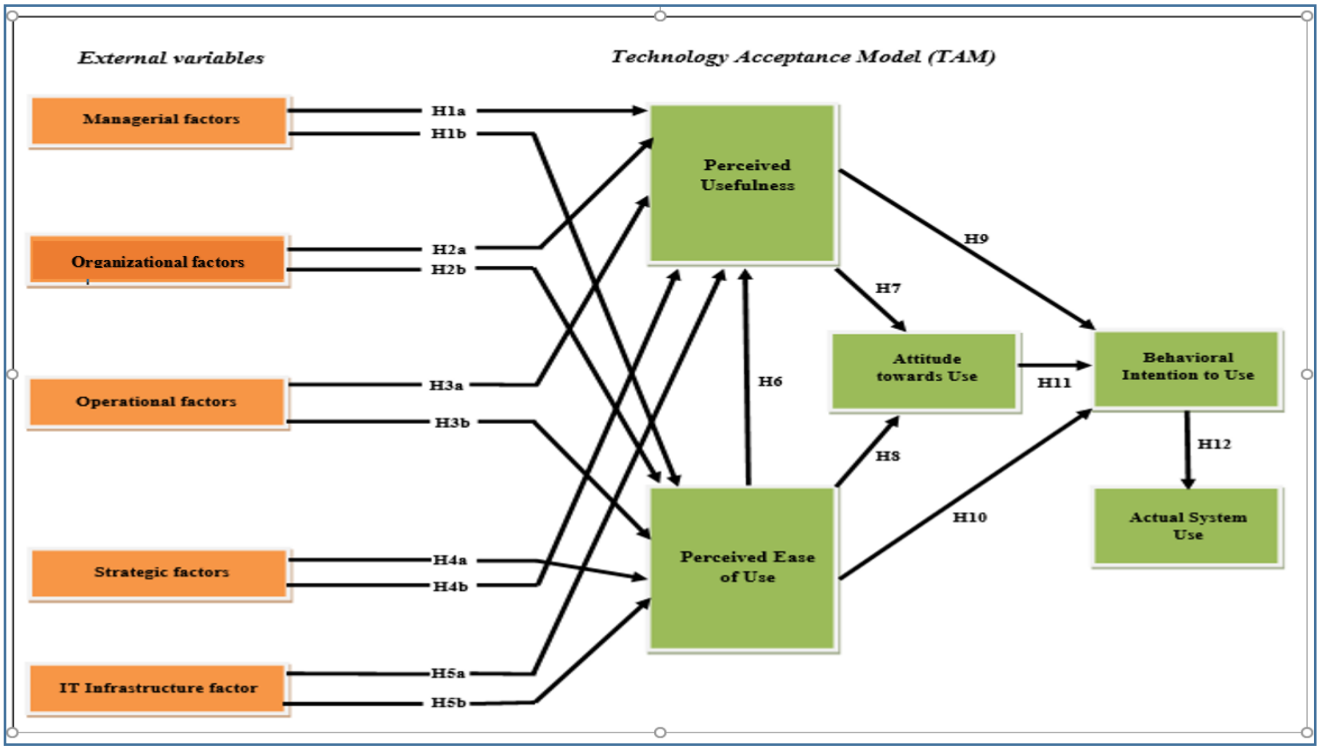

Figure 2. Modified Research Model

Chapter Four

Research Methodology

4.1 Overview

Research methodology chapter presents the analysis of acceptance and adoption of artificial intelligence health projects for this dissertation. The research capitalized on the existing theoretical framework that contains of five fundamental constructs in the literature. The five core constructs of the (TAM) includes perceived ease of use, perceived usefulness, Behavioral intention to use, attitude towards usage and the actual system use of Artificial Intelligence projects in the healthcare. After reviewing a systematic approach for the published research studies in the literature on the most widely used external factors for the extended Technology Acceptance Model were identified in education, Information Technology, healthcare, and business fields. The external factors considered in this dissertation are managerial, operational, organizational, strategic and IT infrastructure. Besides, the Structure Equation Model was employed for this dissertation to gather respondents answers through the online questionnaire. Detailed explanation on the survey structure and research survey design is listed in this chapter.

4.2 Research design

In accordance with this dissertation, two types of research designs were employed for the critical success factors for (AI) projects in the healthcare sector. The first one is the survey design and the second type is the meta-analysis design. Both types are explained deeply as below.

4.3 Survey Design

Starting with survey design structure for this dissertation, in order to obtain the quantitative primary data from respondents. Survey research design has been employed by numerous previous researchers, and it is known as a significant study design in bringing out the attitudes, characteristics, opinions or behaviors of the given population (Brannen 2017). For this particular study, primary data was collected and examined to obtain the most significant critical success factors that impact the implementation of artificial intelligence projects in health domain. Also, 53 participants responded to the online survey questionnaire from different organizations, as the main purpose of using survey research design is to come up with an explanation of employee's attitudes towards artificial intelligence projects in health and IT domains concerning acceptance of artificial intelligence technology in their workplaces. Creswell, and Creswell (2017) states that survey research design is advantageous to the researchers due to capabilities to measure respondent's attitudes.

4.4 Meta-Analysis Design

Meta-analysis design structure assisted in expanding the overall sample size and aligning with the scope of study. According to Moher et al. (2015), the main objective of employing meta-analysis design is to enhance a new overview of the study problem through synoptic reasoning. Therefore, the main reason of employing meta-analysis design is to analyze differences in the research findings among the 23 studies. Meta-analysis design assists in expanding the required precisions while estimating the impacts of the study. Basing on Moher et al. (2015), meta-analysis research that is well designed is dependent on the strict following of the strategies employed when selecting published studies as well as the presence of the data in every study to come up with proper analysis of the findings. However, insufficient data collected using this design compromised on the reliability and generalizable of the study's findings. Furthermore, Nardi (2018) asserts that the more dissimilarity in the findings of the studies under systematic review, the more challenging it is to make justifications of interpretations governing a reliable and credible synopsis of the findings.

4.5 Research Methodology

The research study is seeking to examine and analyze the critical success factors associated with the implementation of (AI) projects in health care sector. Understanding the attitude of project owners and associated employees in implementing (AI) projects for health sectors can assist in comprehending the critical success factors regarding project's strengths and weakness. As hypothesized, the attitude is significant in determining the level of health sector willingness to use artificial intelligence systems in the treatment plans of their respective patients. The setting of the healthcare centers staff and IT professionals that were considered to take part in this study was in the gulf region in United Arab Emirates (UAE), Dubai emirate to be precise. Quantitative data collection method was by answering questions using an online survey questionnaire. Research participants were provided an online link to do the questionnaire within a simplified view of the survey questions, requiring short time less than ten minutes to answer the survey.

4.6 Methodology Challenges

This dissertation experienced different challenges at different stages of its implementation. Most of the methodology challenges were based on the mechanisms of collecting data and their sources. There are no previous credible studies that cover the critical success factors in implementing artificial projects in the healthcare sector. However, this dissertation had to look for most appropriate, credible studies in healthcare and other fields such as Information Technology, business, and education to come up with the list of most widely external factors in extending

(TAM) model. Another methodology challenge for this dissertation was finding willing physicians and project managers in the government and private hospitals within the emirate of Dubai to take part in the interview. Doctors and medical staff are known for having busy schedules attending to various patients. Also, physician's availability is significant in case of any emergency cases and operations. It was, therefore, a challenge to come up with a sample population respondent from a busy population of professionals dealing and monitoring human lives.

4.7 Sample description

The population targeted by this study comprised of both IT and health staff. In total, 53 surveyors were considered to take part in this study. Three health centers in Dubai that physicians selected for the online survey questionnaire were picked from Al Barsha Health Center, Nad Al Hamar Health Center, Al Mamzar Health Centere. The sample population was selected based on the availability of the physicians as the tight schedules of the research participants were put into consideration. The selection of the sample population was conducted using a purposive sampling method. According to Tongco (2007), purposive sampling is a non-probability sampling technique that the researcher has to rely on individual's personal judgment while selecting the members of the sample population to take part in the study. sampling technique is known for coming up with a population that aims at providing clear information to serve a given purpose. That is why only health and IT staff from registered healthcare centers in Dubai were involved in answering the survey questionnaire.

4.8 Data Collection Methods and Tools

The quantitative data analyzed in this dissertation was collected with association of the questionnaire survey administered online. Specifically, research participants were provided an online link to access the survey dashboard from which they gave their responses. The Structural Equation Modeling was used to evaluate the measurement model validity and the reliability to fit the model. But it only succeeded final path model that had been utilized before.

4.9 Study Instrument

A survey instrument was developed to test the hypotheses formulated concerning the findings of this dissertation. Technology Acceptance Model constructs were measured using different questions on the stated factors. Below table identifies the distribution of questions based on the five factors shown.

PART	**Factors**	**Number of questions**
2	Managerial Factors	3
3	Operational Factors	2
4	Strategic Factors	2
5	IT Infrastructure Factors	4
6	Organizational Factors	4

Table 2. Study Factors Table

4.10 Survey Structure

As aforementioned above, this particular research study relied on a questionnaire survey to collect data from the participants. After being developed, the questionnaire survey was uploaded online, and respondents were provided with the link. Generally, the questionnaire was structured in such a way that it captured all the items that could provide precise data concerning critical success factors for implementing Artificial Intelligence projects in the healthcare sector. Structurally, the survey tool was segmented into six different parts. Part one only comprised of demographic information regarding the research respondents. Part two addressed managerial factors as Part three captured prompts on operational factors. Strategic factors, IT infrastructure factors and organizational factors were placed in part four, five and six respectively. In all the parts, there were at least three questions that asked participants on their perceptions about the factors. In total, the questionnaire survey utilized in this dissertation study has 28 items. Again, the survey used a 5-point Likert scale with multiple choices structured as follow: 1-strongly Agree, Agree, Neutral, Disagree and Strongly Disagree.

4.11 Ethical consideration

Ethical consideration is very important while conducting any research study adhered to the integrity of the highest degree by observing the ethical standards of research projects. It is the adherence to the codes of ethics that enabled the researcher to stage not only a reliable but also a valid research study that attained justifiable research findings. As Kamat (2016) describes, it is a necessity for the researchers to observe all the ethical implications associated with the individual study. Based on the sample population selected, respondents were contacted at personal levels to be informed of the reasons for being considered to take part in this dissertation. Furthermore, the research observed human codes of ethics by ensuring the confidentiality of the responses given by the research participants, ensuring the privacy of the personal data for the respondents. Moreover, all the published data sources from which the data supporting primary findings were obtained from were credible. Since it was built on strong pillars of ethical considerations, this particular research will come up with the critical success factors for implementing (AI) projects within the health sector. Therefore, the findings will be employed to enhance healthcare system in Dubai and other emirates within UAE.

In addition, survey results will contribute to answer this dissertation question and target its aims. The drawn questions in the survey and segmented parts of it drives the answers for each aim in the research. First, it will explore factors for implementing artificial intelligence projects for health care sector in Dubai using the technology acceptance model. Second, it will investigate the critical success factors within health sector projects and the relationship between these critical factors with the artificial intelligence projects.

4.12 Summary

Methodology chapter provided a comprehensive information on the strategies that were employed to answer the research questions concerning the critical success factors for implementing artificial intelligence projects in healthcare. The current study adopted a quantitative method of data collection as research participants were required to answer an online questionnaire survey. In total, 53 health and IT staff took part in the current study. Selection of the participants was through purposive sampling as it provides both reliable and valid findings because of its nature of choosing the only population based on the researchers' perceptions of the research topic.

Chapter Five

Discussion of the Results

5.1 Overview

Results chapter provides research findings obtained from the online conducted survey questionnaire. The first part of this chapter depicts the employee's personal information or rather demographic data, including gender, age, level of education, profession, job title, work experience, sector, and role in the organization. Besides, the questionnaire pilot study was conducted and results are presented. In the Partial least square analysis methodology, there was an assessment of the measurement model (Outer model) and the structural model (Inner model). Assessment of the inner model comprised of examining the convergent and divergent validities the composite reliabilities were found to range between 0.777 and 0.922. In the inner model, the coefficient of determination and test of hypotheses were done as presented in the results.

5.1.1 Employees' personal information / Demographic Data

As stated in the methodology chapter, the first prompts of the questionnaire asked respondents of this particular study on their demographic data. It can be said that 74% of the participants were females with only 26% of the respondents being males as shown in Figure 3 below.

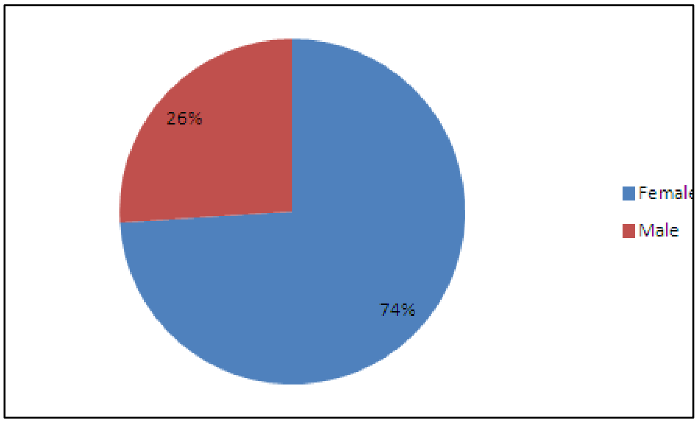

Figure 3. Gender distribution

Based on ages, 39 respondents were between 25 and 34 which represent 74% of the total population of the IT and health staff that took part in this study. Besides, 1 respondent was between 18 and 24 years while 13 out of the total of 53 participants were between 35 and 45 years old in figure 4 captures this information.

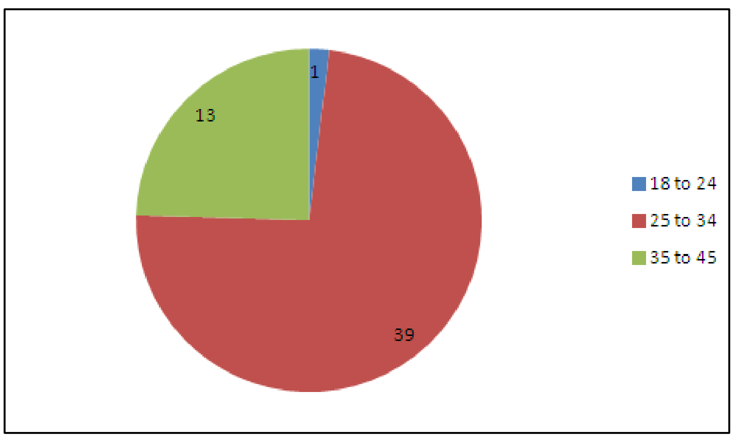

Figure 4. Employee Age

The level of education was the third prompt that respondents gave their demographic data on. In this dissertation, 13% of participants had a diploma, 38% Bachelor, 45% Master and 4% Doctorate qualifications as presented in Figure 5 below.

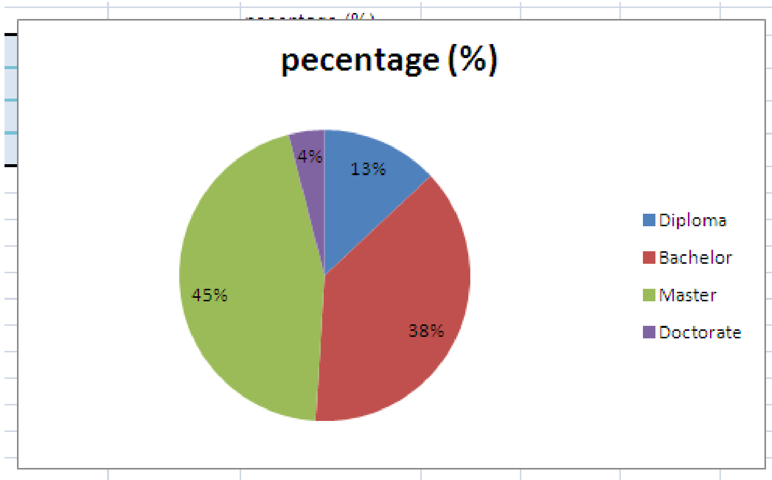

Figure 5.Level of education

On the other hand, Figure 6 shows the sector in which the respondents worked in based on government (60%), semi-government (25%) and private (15%).

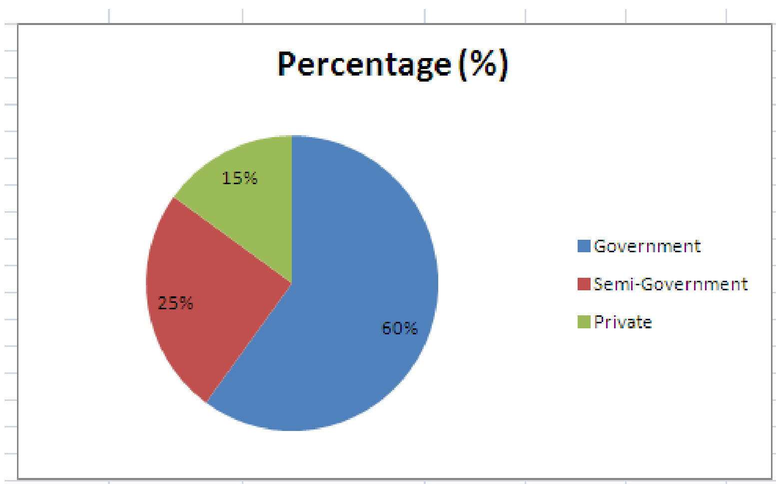

Figure 6. Sector distribution

Furthermore, Information Technology is the profession that had a larger representation of the research participants in this study with a population of 29 out of 53. The business profession had 9 individuals, project management had 4 individuals and the rest are captured in Figure 7 below.

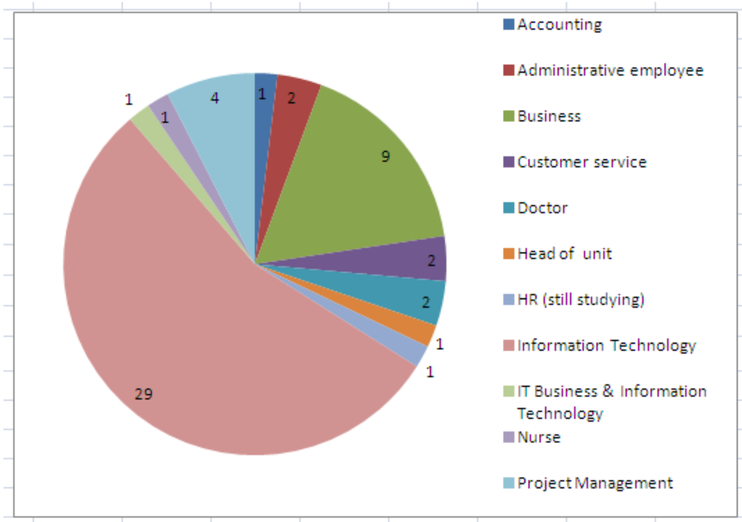

Figure 7. Profession distribution

Figure 8 shows variations in the job titles of the respondents. In this study, 25% of the respondents were IT professionals as 21% had IT support titles. IT Managers were 19% as both IT engineers and project leaders represented 15% each of the population. The least represented job title in this study was IT supervisors which were only 6% of the entire population.

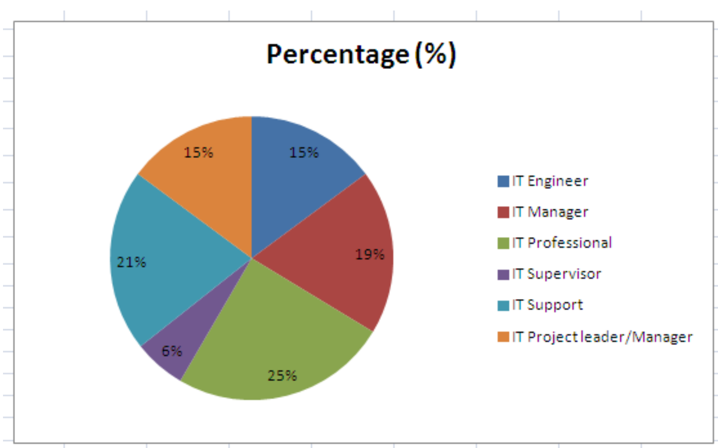

Figure 8. Job title

Figure 9 shows the roles that participants were playing in their respective organizations. Higher management, junior level, managerial level, and senior/professional level had representations of 5,7,14 and 27 respondents out of the total of 53 participants.

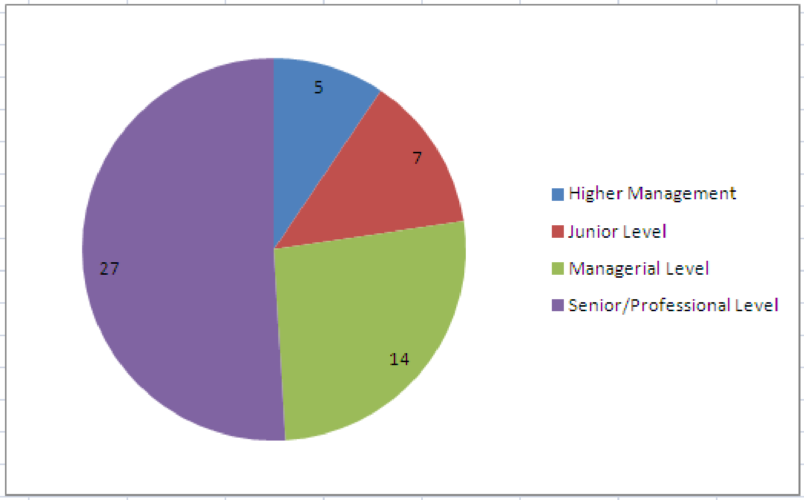

Figure 9. Role in the organization

It can also be said that 42% of the participants had 4-7 years of experience in their jobs while 25% of the respondents had 0-3 years of work experience. As shown in figure 10, 34% had work experience of 10 years and above.

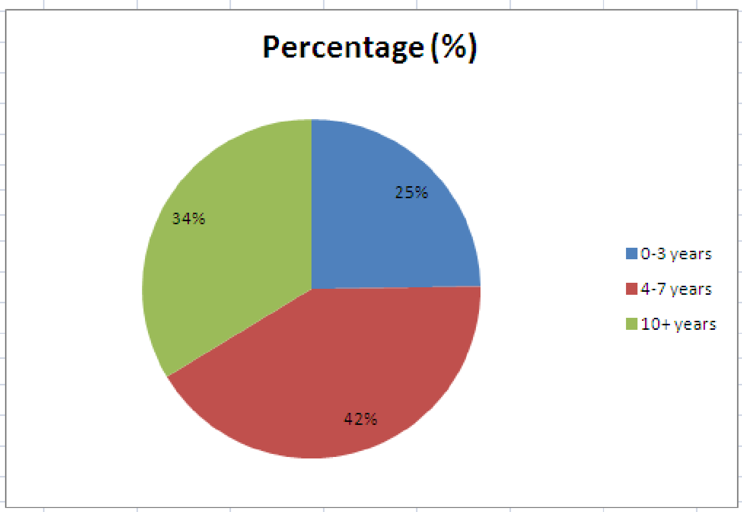

Figure 10. Job experience in years

Elsewhere, 81% of the respondents were of the opinion that (AI) would increase the healthcare performance levels in Dubai with only 2% having contrary views. However, 15% of the participants were not sure as to whether implementing (AI) projects would increase the healthcare in Dubai, information is presented in Figure 11.

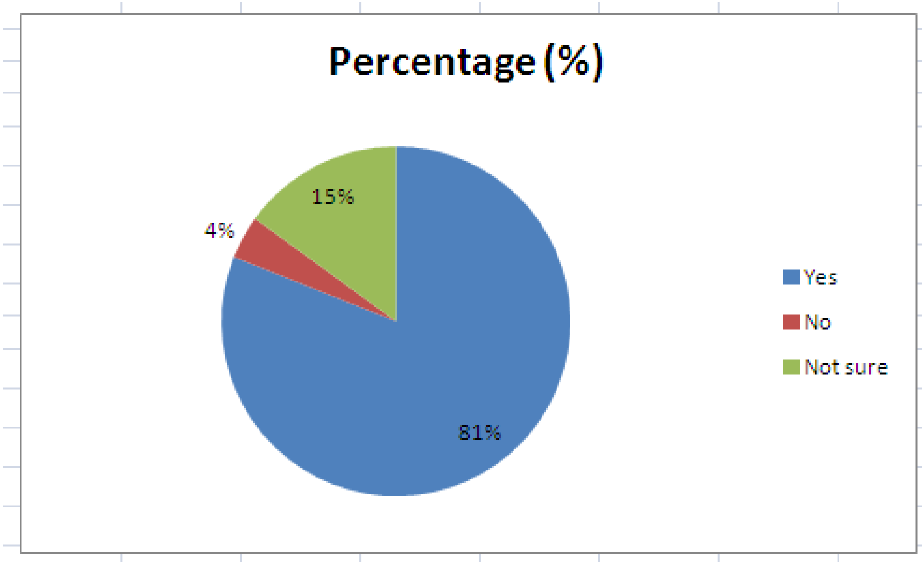

Figure 11. AI projects would increase the healthcare performance levels in Dubai

Lastly, 60% of respondents acknowledged the difference between (IT) and (AI) projects while 8% said “No” to this prompt. particular prompt also had 32% of the population stating as not to be sure if there was a difference between IT and AI projects as captured in Figure 12.

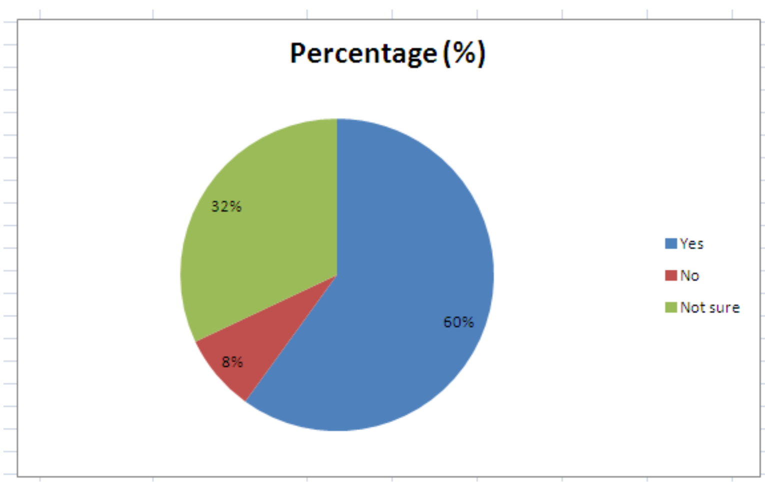

Figure 12. Difference between IT and AI Projects

5.2 Questionnaire Pilot Study

Before carrying out the actual survey, a pilot study was conducted with an aim of measuring the reliability of the items in the questionnaire articularly considered 10 health and IT staff that were selected randomly from the defined population in the Dubai-based health centers. The internal reliability of the TAM's constructs was measured using the Cronbach's alpha. Alrawashdeh, Firstauthor and Secondcoauthor (n.d) state that any reliability coefficient equivalent to or above 0.70 is acceptable in the research studies. And as noted, all the constructs in this study had a reliability coefficient of over 0.70 as depicted in the table below. Thus, 100% of the constructs were deemed reliable and used in the final study.

Construct	Cronbach's alpha
Managerial factors	0.725
Organizational factors	0.798
Operational factors	0.823
Strategic factors	0.789
IT Infrastructure factor	0.950
Perceived Usefulness	0.777
Perceived Ease of Use	0.765
Attitude towards usage	0.808
Behavioral intention to use	0.858
Actual System Use	0.751

Table 3. Reliability coefficients from Cronbach's alpha

5.3 Partial least square analysis methodology

5.3.1 Assessment of the measurement model (Outer model)

The Smart PLS for Partial Least Squares Structural Equation Modeling (PLS-SEM) software was considered appropriate in this study as it is not only accessed and used freely by researchers and academics but also it has a user interface that is friendly with reporting features that are of advanced level. The PLS-SEM tool was developed by Ringle, Wende and Will (2005) and since then it has become more popular as stated by Wong (2013). Measurement model is responsible for describing the relationship that links indicators to the latent construct. But Chin (1998) proposes discriminate and convergent validities as the two validities that are required to evaluate the measurement model. The convergent validity helps in determining the level that constructs perceived to be theoretically similar are related. On the other hand, the level at which such constructs differ from one another is determined by the discriminate validity. It can, therefore, be stated that both discriminate and convergent validities provide evidence for the effectiveness of the measurement model.

5.3.2 Convergent validity

In this particular study, two approaches were employed while evaluating the convergent reliability. It is the analysis of the individual measures' loadings that was done first before composite reliabilities were determined. The first process was done based on the corresponding constructs of the individual measures. The Partial Least Squares (Smart PLS ver. 3.2.6) was employed to determine the convergent validity. Besides, a pair of analyses was conducted in which the initial PLS operation that used boot trapping approach comprised of 300 resamples was significant in creating loadings, t-values, weights, average variance extracted (AVE) and composite reliabilities for each item of measurement that aligned with its anticipated construct (S. A. Salloum, Al-Emran, Shaalan, & Tarhini, 2018.A relatively higher value was obtained in every measurement item whose loadings were evaluated rather than the 0.70 suggested (Chin 1998; Hair Jr et al. 2016). As indicated in the table below, it was depicted that loadings for each measurement item were very as compared to the 0.70 value that is recommended. According to Chin (1998), 0.70 or a higher value show that the measurement item shares a variance of over 50% with its hypothesized construct. In the table below, composite reliabilities, average variance extracted and subsequent number of each item are depicted. Moreover, the 0.70 composite reliabilities value makes the internal consistency to be satisfactory. A keen look at the table below also shows that the individual values range between 0.777 and 0.922. It is also important to note that the Cronbach's alpha score for each of the TAM's constructs was above 0.70 showing that they all met the reliable measure.

Constructs	Items	Factor Loading	Cronbach's Alpha	CR	AVE
Managerial factors	MF1	**0.921**	**0.873**	**0.922**	**0.797**
	MF2	**0.894**			
	MF3	**0.862**			
Organizational factors	TF1	**0.773**	**0.771**	**0.797**	**0.569**
	TF2	**0.807**			
	TF3	**0.876**			
Operational factors	OF1	**0.898**	**0.800**	**0.885**	**0.723**
	OF2	**0.929**			
	OF3	**0.706**			
Strategic factors	SF1	**0.960**	**0.791**	**0.828**	**0.619**
	SF2	**0.861**			
	SF3	**0.825**			
IT Infrastructure factor	IF1	**0.829**	**0.842**	**0.905**	**0.761**
	IF2	**0.900**			
	IF3	**0.887**			
Perceived Usefulness	PU1	**0.874**	**0.787**	**0.875**	**0.701**
	PU2	**0.759**			
	PU3	**0.874**			
Perceived Ease of Use	PEOU1	**0.887**	**0.864**	**0.777**	**0.527**
	PEOU2	**0.852**			
	PEOU3	**0.862**			
Attitude towards use	AT1	**0.772**	**0.706**	**0.830**	**0.619**
	AT2	**0.777**			
	AT3	**0.811**			
Behavioral intention to use	BI1	**0.798**	**0.821**	**0.897**	**0.748**
	BI2	**0.929**			
	BI3	**0.945**			
Actual System Use	AU1	**0.938**	**0.803**	**0.909**	**0.833**
	AU2	**0.887**			

Table 4. Convergent validity results which assures acceptable values (Factor loading, Cronbach's Alpha, composite reliability >= 0.70 & AVE > 0.5)

5.3.3 Discriminate validity

According to Chin (1998), discriminate validity is used to determine the level at which an individual construct differs from other constructs within any given research model. In this particular study, discriminate validity was conducted with the help of two distinct processes. The analysis of the correlations of the measurements of the latent variable with the measurement items was done. Constructing measures were differentiated from one another to obtain the discriminate validity. However, powerful loading is supposed to be shown by the measures regarding their anticipated construct rather than other constructs in the given research model showing the loadings are expected to be of higher values than the cross-loadings. Furthermore, the evaluation of the average variance extracted was done to ensure that each construct has a greater variance with its measures whenever it is compared to other latent constructs in the (TAM) research model. It is important to note the square root of the average variance extracted for every construct is normally higher if it is compared the common variance among the model's constructs. And this value should again be higher than 0.5 as Fornell and Larcker (1981) noted. It is thus proposed that a construct should find at least half of the measurement variance if the average variance extracted is above 0.5. As aforementioned above, the Partial Least Squares (SmartPLS ver. 3.2.6) was utilized while evaluating the discriminate value in this study. In the table below, both loadings and cross-loadings are shown. Cheng and Chen (2015) explain that the in-depth analysis of both loadings and cross-loadings depicts that all measurement item load broadly based on their respective latent constructs rather than the loading of other constructs. Table 3 below shows the AVE analysis. In this table, the AVE scores' square roots are presented in the bold diagonal table constituents whereas the constructs' correlations are presented in the offload diagonal table constituents. By lying between 0.837 and 0.926, the AVE values' square roots are perceived to be higher as compared to the 0.5

which is a suggested value. According to Hair Jr et al. (2016), the average variance extracted is usually higher than other correlations with the model's constructs. In this case, there is a vivid depiction of the greater variance of each construct with its measures instead of other constructs in the (TAM) model, hence resulting to a discriminate validity.

5.3.4 Heterotrait-Monotrait Ratio of Correlations (HTMT)

The Heterotrait-monotrait ratio of the correlations (HTMT) is an approach that has been heavily employed in the recent past when examining the discriminate validity as Henseler, Ringle and Sarstedt (2015) explain. According to Henseler et al. (2015), the HTMT can be said to be the heterotrait-heteromethod correlations that align directly with the average of the monotrait-heteromethod correlations. Notably, HTMT is the latest approach to evaluating discriminate validity in the PLS-SEM to be developed. s is an important pillar when it comes to the model examination. Failure to determine discriminate validity presents researchers in a dilemma as they are unable to understand if the findings on the hypothesized structural paths are accurate or marred with the statistical discrepancies. Moreover, the HTMT has been considered to be effective as compared to the traditional approaches like partial cross-loadings and Fornell-Larcker method. is because the traditional approaches are unable to determine the absence of discriminate validity as stated by Campbell and Fiske (1959). Importantly, the true correlation between a pair of the model's constructs is shown as distinct if the HTMT values are below 1. But values above 1 show the absence of the discriminate validity. However, some researchers foster as the threshold of 0.85 as others propose 0.90 (Kline 2011; Teo, Srivastava & Jiang 2008). In Table 5, the HTMT technique is shown and it is suggested that each construct has a higher variance with its respective measures other than other model's constructs, hence resulting to discriminate validity.

	Actual System Use	AT	BI	IF	MF	OF	PEOU	PU	SF	TF
Actual System Use	**0.913**									
AT	0.417	**0.887**								
BI	0.301	0.478	**0.865**							
IF	0.178	0.253	0.246	**0.872**						
MF	0.321	0.222	0.322	0.216	**0.893**					
OF	0.133	0.119	0.250	0.533	0.278	**0.850**				
PEOU	0.129	0.177	0.120	0.665	0.296	0.418	**0.926**			
PU	0.085	0.259	0.128	0.294	0.315	0.497	0.684	**0.837**		
SF	0.040	0.234	0.305	0.449	0.325	0.660	0.373	0.531	**0.887**	
TF	0.165	0.422	0.480	0.501	0.613	0.686	0.419	0.555	0.526	**0.854**

Table 5. The Fornell-Larcker Scale

	Actual System Use	AT	BI	IF	MF	OF	PEOU	PU	SF	TF
AU1	**0.938**	0.482	0.923	0.095	0.011	0.105	0.033	0.082	0.036	0.142
AU2	**0.887**	0.464	0.695	0.039	0.016	0.144	0.018	0.073	0.038	0.165
AT1	0.245	**0.772**	0.350	0.075	0.037	0.063	0.159	-0.050	0.082	0.042
AT2	0.293	**0.777**	0.485	0.020	0.013	0.005	0.160	0.048	0.035	0.026
AT3	0.588	**0.811**	0.679	0.041	0.015	0.004	0.114	0.044	0.009	0.046
BI1	0.540	0.738	**0.798**	0.088	0.040	0.050	0.145	0.128	0.098	0.022
BI2	0.480	0.503	**0.929**	0.109	0.014	0.094	0.054	0.113	0.061	0.113
BI3	0.484	0.543	**0.945**	0.080	0.032	0.072	0.020	0.065	0.010	0.103
IF1	0.033	0.091	0.014	**0.829**	0.256	0.542	0.559	0.645	0.459	0.490
IF2	0.091	0.003	0.091	**0.900**	0.180	0.434	0.611	0.690	0.366	0.411
IF3	0.077	0.049	0.041	**0.887**	0.135	0.426	0.571	0.541	0.355	0.414
MF1	0.019	0.006	0.021	0.213	**0.921**	0.263	0.298	0.298	0.385	0.580
MF2	0.069	0.018	0.043	0.169	**0.894**	0.176	0.213	0.254	0.205	0.516
MF3	0.036	0.016	0.070	0.192	**0.862**	0.292	0.271	0.287	0.260	0.538
OF1	0.148	0.001	0.069	0.453	0.201	**0.898**	0.378	0.392	0.472	0.634
OF2	0.120	0.021	0.036	0.495	0.177	**0.929**	0.420	0.439	0.555	0.649
OF3	0.066	0.028	0.020	0.403	0.347	**0.706**	0.253	0.439	0.667	0.451
PEOU1	0.101	0.023	0.079	0.652	0.287	0.372	**0.887**	0.683	0.397	0.451
PEOU2	0.036	0.121	0.009	0.526	0.240	0.380	**0.852**	0.523	0.253	0.295
PEOU3	0.302	0.494	0.433	0.069	0.024	0.030	**0.862**	0.079	0.050	0.008
PU1	0.083	0.031	0.054	0.581	0.183	0.418	0.557	**0.874**	0.375	0.440

PU2	0.005	0.053	0.052	0.513	0.327	0.350	0.434	**0.759**	0.427	0.448
PU3	0.118	0.067	0.051	0.577	0.300	0.471	0.501	**0.874**	0.534	0.508
SF1	0.024	0.017	0.016	0.222	0.326	0.461	0.218	0.344	**0.960**	0.386
SF2	0.089	0.029	0.027	0.374	0.314	0.599	0.249	0.410	**0.861**	0.474
SF3	0.008	0.033	0.021	0.429	0.168	0.503	0.383	0.479	**0.825**	0.391
TF1	0.115	0.037	0.085	0.285	0.515	0.275	0.289	0.389	0.292	**0.773**
TF2	0.151	0.041	0.063	0.325	0.670	0.410	0.287	0.425	0.337	**0.807**
TF3	0.107	0.022	0.035	0.500	0.218	0.815	0.361	0.430	0.535	**0.876**

Table 6. Results of Cross-loading

	Actual System Use	**AT**	**BI**	**IF**	**MF**	**OF**	**PEOU**	**PU**	**SF**	**TF**
Actual System Use										
AT	0.630									
BI	0.155	0.575								
IF	0.089	0.090	0.128							
MF	0.055	0.036	0.065	0.253						
OF	0.168	0.078	0.104	0.653	0.337					
PEOU	0.330	0.774	0.456	0.454	0.390	0.582				
PU	0.102	0.082	0.148	0.466	0.387	0.626	0.121			
SF	0.074	0.108	0.103	0.572	0.422	0.236	0.556	0.711		
TF	0.237	0.102	0.132	0.684	0.243	0.277	0.662	0.792	0.497	

Table 7. HTMT technique

5.3.5 Assessment of structural model (Inner model)

After determining the relevance of the measurement model, the examination of the structural model was conducted. It is after this process that testing of the hypothesis was done. Based on the provisions of a structural model, a causal relationship among the latent constructs of the (TAM) exists. In this particular study, the initial analysis of the structural model was done by identifying the predictive capacity of the research model. Hair Jr et al. (2016) show that it is significant to analyze the anticipated relationships among the latent constructs of the (TAM) research model presented. As the dependent variable's R-square is used to determine the predictive power of the

(TAM) model, the path coefficients, on the other hand, are employed to carry out the examination of the hypothesized relationships' capability. The validation process of the structural model in this study was done with the help of PLS-Graph (SmartPLS ver. 3.2.6). Figure 2 captures the results of the PLS-Graph output.

5.3.6 Coefficient of determination -R^2

A coefficient of determination or as commonly referred to as 'R^2'is the popular measure that is employed while analyzing the structural model (Dreheeb, Basir, & Fabil 2016; Salloum & Shaalan, 2018). It is called by the measure upon while determining the predictive accuracy of the (TAM) model. Senapathi and Srinivasan (2014) state that this measures are presented as a squared correlation between the specific actual as well as predictive values of the endogenous construct. Besides, this measure shows the level of variance in such constructs as are validated be each related construct. Chin (1998) recommends that an R2 value more than 0.67 is high, between 0.33 and 0.67 to be moderate and between 0.19 and 0.33 should be said to be weak.

According to Table 6, the R2 values for the behavioral of actual system use, attitude towards use, behavioral intention to use, perceived ease of use, and perceived usefulness were found to be between 0.33 and 0.67; and hence, the predictive power of these constructs is considered as moderate.

Constructs	**R^2**	**Results**
Actual System Use	0.636	Moderate
Attitude towards use	0.519	Moderate
Behavioral intention to use	0.392	Moderate
Perceived Ease of Use	0.422	Moderate
Perceived Usefulness	0.464	Moderate

Table 8. Endogenous latent variables'

5.3.7 Test of the hypotheses - Path coefficient

To analyze the various hypothesized associations, the structural equation modeling was used (see Table 7). (Al-Emran & Salloum, 2017; Milošević, Živković, Manasijević, & Nikolić, 2015) stated that the values of fit indices that were computed showed that there was the suitable fit of the structural model to the data for the given research model. As per the opinion of (Milošević et al., 2015) this study recommends the intended values of fit indices, there is fitting structural model fit to the data for the research model (S. A. Salloum, Al-Emran, Shaalan, & Tarhini, 2018; S. A. S. Salloum & Shaalan, 2018) (see Fig. 2). It can be seen in the Table 9 that all the values were in the given range. In addition to it, few direct hypotheses also showed support (Ma & Yuen, 2011). The resulting path coefficients of the suggested research model are shown in Figure 13. Generally, the data supported sixteen out of seventeen hypotheses. All endogenous variables were verified in the model (PU, PEOU, AT, BI, and AU). Based on the data analysis hypotheses H1a, H2a, H3a, H3b, H4a, H5a, H5b, H6, H7, H8, H9, H10, H11, and H12 were supported by the empirical data, while H4b was rejected. The results showed that Perceived Usefulness significantly influenced Managerial factor (β= 0.312, $P<0.05$), organizational factors (β= 0.189, $P<0.05$), Operational factors supporting (β= 0.147, $P<0.05$), Strategic factors (β= 0.206, $P<0.05$), IT Infrastructure factor (β= 0.527, $P<0.001$) and Perceived Ease of Use (β= 0.242, $P<0.001$), hypothesis H1a, H2a, H3a, H4a, H5a and H6 respectively. Perceived Usefulness and Perceived Ease of Use were determined to be significant in affecting Attitude towards use (β= 0.116, $P<0.001$) and (β= 0.256, $P<0.001$) supporting hypotheses H7 and H8. Perceived Usefulness and Perceived Ease of Use were determined to be significant in affecting Behavioral intention to use (β= 0.502, $P<0.001$) and (β= 0.105, $P<0.01$) supporting hypotheses H9 and H10. Furthermore, Perceived Ease of Use was significantly influenced by four exogenous factors: Managerial factor (β= 0.163, P < P<0.05), organizational factors (β= 0.139, P<0.05), Operational factors (β= 0.255, P<0.05), and IT Infrastructure factor (β= -0.605, P<0.001) which support hypotheses H1b, H2b, H3b, H4b and H5b. The relationship between Strategic factors and Perceived Ease of Use (β= 0.033, P=0.696) is statistically not significant, and Hypotheses H4b is generally not supported. Finally, the relationship between Attitude towards use and Behavioral intention to use (β= 0.697, P<0.001) is statistically significant, and Hypotheses H11 is generally supported, and the relationship between Behavioral intention to use and Actual System Use (β= 0.901, P<0.001) is statistically also significant, and Hypotheses H12 supported. A summary of the hypotheses testing results is shown in Table 9.

Hyp.	Relationship	Path	*t*-value	*p*-value	Direction	Decision
H1a	Managerial factor -> Perceived Usefulness	0.312	3.235	0.015	Positive	Supported*
H1b	Managerial factor -> Perceived Ease of Use	0.163	2.163	0.031	Positive	Supported*
H2a	Organizational factors -> Perceived Usefulness	0.189	2.499	0.013	Positive	Supported*
H2b	Organizational -> Perceived Ease of Use	0.139	4.405	0.035	Positive	Supported*
H3a	Operational factors -> Perceived Usefulness	0.147	1.873	0.042	Positive	Supported*
H3b	Operational factors -> Perceived Ease of Use	0.255	1.604	0.046	Positive	Supported*
H4a	Strategic factors -> Perceived Usefulness	0.206	3.129	0.002	Positive	Supported*
H4b	Strategic factors -> Perceived Ease of Use	0.033	0.391	0.696	Positive	Not supported
H5a	IT Infrastructure factor -> Perceived Usefulness	0.527	7.428	0.000	Positive	Supported**
H5b	IT Infrastructure factor -> Perceived Ease of Use	0.605	7.197	0.000	Positive	Supported**
H6	Perceived Ease of Use -> Perceived Usefulness	0.242	3.268	0.001	Positive	Supported**
H7	Perceived Usefulness -> Attitude towards use	0.116	4.737	0.004	Positive	Supported**
H8	Perceived Ease of Use -> Attitude towards use	0.256	6.883	0.008	Positive	Supported**

H9	Perceived Usefulness -> Behavioral intention to use	0.502	7.036	0.005	Positive	Supported**
H10	Perceived Ease of Use -> Behavioral intention to use	0.105	7.379	0.006	Positive	Supported**
H11	Attitude towards use -> Behavioral intention to use	0.697	17.897	0.000	Positive	Supported**
H12	Behavioral intention to use -> Actual System Use	0.901	77.891	0.000	Positive	Supported**

Table 9. Results of structural model (significant at p** < = 0.01, p* < 0.05).

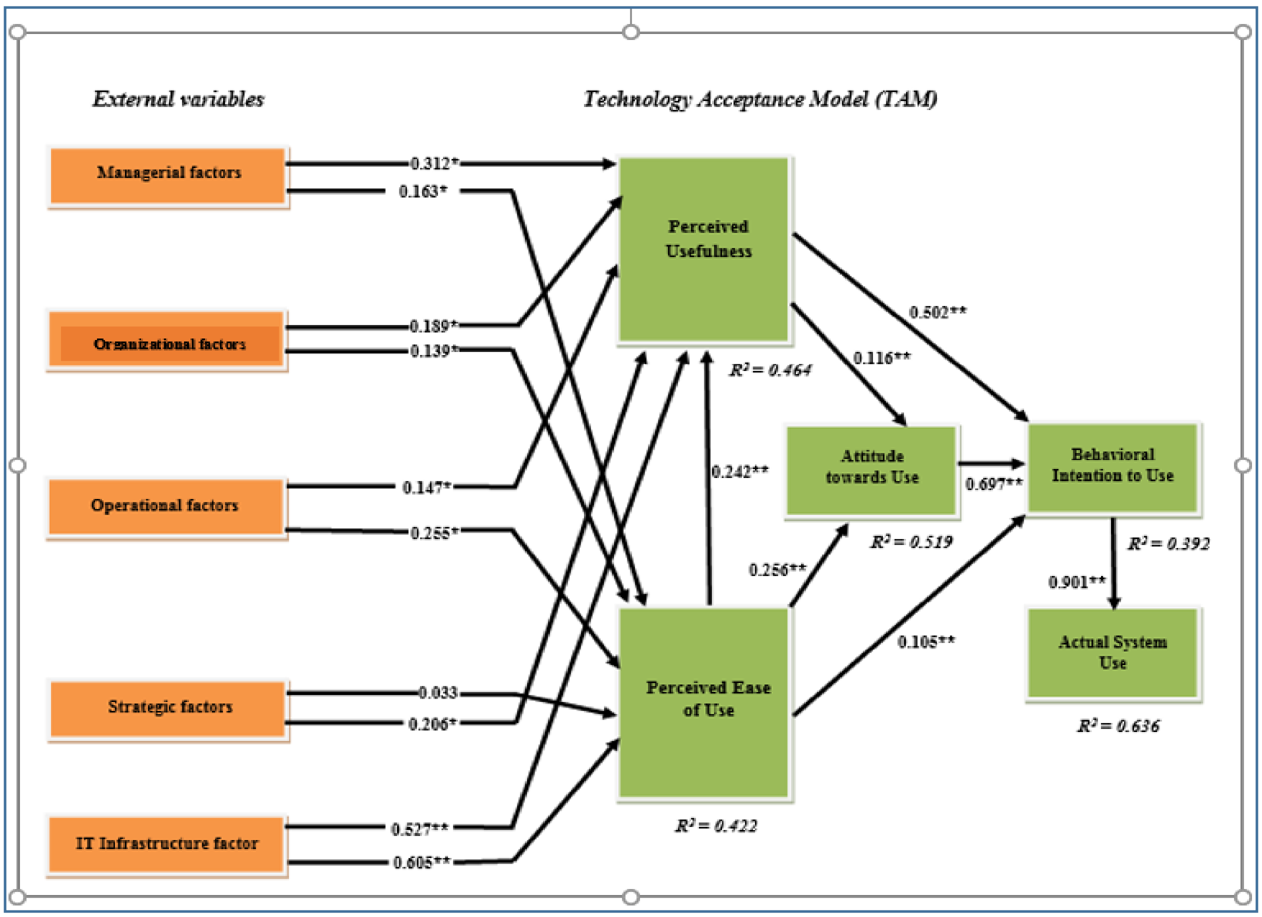

Figure 13. Coefficient results have (significant at p** < = 0.01, p* < 0.05).

5.4 Discussion

During this study, it was analyzed that the most successful factors that can be used for establishing artificial intelligence projects within the healthcare sector are (managerial, operational, organizational, strategic and IT infrastructure). The fundamental purpose of conducting this research paper is to investigate the mentioned critical success factors in parallel for AI projects that have never been discussed within any of the literature papers that were gathered based on the measurements of this study. Beside, Structure equation modeling (PLS-SEM) was equip to investigate the accuracy of this research hypotheses. The Smart PLS for Partial Least Squares Structural Equation Modeling (PLS-SEM) software as a measurement model employed to illustrates the relationship that links indicators to the latent construct. The total number of cases dedicated to bootstrapping in the current study involves 300 cases that are suitable for the sample size. The total outcome of the analyzed seventeen hypotheses were provided in Table 3. The coefficient of determination -R^2, refers to the values that are part of the variance in the actual variable and the predictable variables of the endogenous constructs. Chin (1998) proposed that an R2 value more than 0.67 is high, between 0.33 and 0.67 to be moderate and between 0.19 and 0.33 is weak area. According to Table 8 the Endogenous variables' R2 for actual system use, attitude toward use, Behavioral intention to use, perceived ease of use and perceived usefulness were resulted between 0.636 and 0. 464 and the results are moderate power for all of it. Also, the Coefficient relation of variables showed the various hypothesized associations, the model of structural equation was utilized and the results illustrated that out of the seventeenth hypothesis all of it were supported except one hypothesis. It was found during this dissertation that perceived Usefulness significantly influenced Managerial factor organizational factors, Operational factors, Strategic factors, IT Infrastructure factor and the

Perceived Ease of Use hypothesis H1a, H2a, H3a, H4a, H5a and H6 respectively. Perceived Usefulness and Perceived Ease of Use were determined to be significant in affecting Attitude towards use supporting hypotheses H7 and H8.

Perceived Usefulness and Perceived Ease of Use were determined to be significant in affecting Behavioral intention to use (supporting hypotheses H9 and H10. Furthermore, Perceived Ease of Use was significantly influenced by four exogenous factors: Managerial factor, organizational, Operational factors and IT Infrastructure factor which support hypotheses H1b, H2b, H3b, and H5b. However, the relation between perceived ease of use and strategic factor H4b was not supported at all as measured to be (β= 0.033, P=0.696). In general, all the proposed hypothesis is sharing positive relationships except one of it.

Finally, Project managers and users in the health domain must consider full focus on those factors while planning for artificial intelligence projects within their firm. factors will enhance artificial intelligence project success rate and possibilities and it will help in implementing more rewarding projects that supports individual's health conditions.

Chapter Six

Conclusion and Future work

6.1 Overview

In conclusion, a systematic review for 23 research studies published between (2015-2018) mixed of quantitative and qualitative research studies were reviewed deeply to fit this dissertation in order to answer the research question for the critical success factors for implementing artificial intelligence projects within the health sector in Dubai with respect of the modified (TAM) research model. Total of 56 external factors were analyzed and assessed and only few factors were considered to be widely used in fostering technology acceptance among the user groups. Moreover, the conducted review for the studies illustrated the acceptance factors for users to implement artificial intelligence projects in their environment. The practices of artificial intelligence projects in health domain was varied either in the medication aspects, patient diagnoses, certain medical tests and predication of future diseases. Besides, different constructs explored in the 23 research studies were collected together to end up with a list of the most widely used external factors that are relied upon frequently during the process of adopting the technology. Furthermore, a modified research model framework was proposed to fit in this dissertation with respect of the Technolgoy Acceptance Model (TAM). Five factors (managerial, strategic, operationa, organizationa and IT infrastructre) and (TAM) constructs (ease of use, percieved usefulness, attitude toward using, behavioral intention, actual system use were reviewd with total of 17 hypothesis proposed for this dissertation.

Data collection process was linked of both exploratory and empirical research method. Primary data were gathered based on the mixed methodology as secondary information in order to support the primary findings referring to the literature review published studies and the designed survey was employed to collect quantitative primary data. Also, data collection tool was through an online questionnaire employed to gather employee's responses who are working in IT and health sector in UAE. Online questionnaire resulted in having 53 respondents. Besides, to analyze the gathered data, structural equation model (SEM) tool was used to evaluate the measurement model that resulted in the emergence of the final path model, using SmartPLS version 3.3.7. Besides, collected results for this dissertation supported the proposed hypothesis a total of sixteen were suited out of seventeen. The most widely external factors were examined as following, perceived usefulness, perceived ease of use, attitude towards use, behavioral intention to use and actual system use.

6.2 Conclusion and future work

First, an analyzes used for (TAM) external factors by reviewing 23 literature studies in different segments such as, health care, education and government within year range of 2015 and 2018. Second, after discovering most of the factors with the use of (TAM) extension, a new model was initiated to support this dissertation paper. Third, a proper suitable assessment for the new model was through the use of fit approach called PLS-SEM. Moreover, survey questionnaire employed to gather the required data and the target audience for this survey were health and IT staff working in different entities and the total number of participants was 53 employees. Total of 17 hypotheses 16 out of it was supported to this dissertation and the findings illustrates positive relation between the factors and the variables of the model. Managerial factors, organizational factors, operational factors and IT infrastructure factors demonstrated a positive relationship with the Perceived Ease of Use and Perceived Usefulness. However, the strategic factors illustrated a negative relationship with the Perceived Ease of Use. Different adaptions have been left for future research to be examined due to time shortage (interview physicians, doctors and health staff is usually time and effort consuming, requiring long process and procedures. It could be significant if future studies consider only government hospitals across UAE and propose a unique modified model with respect to the physicians practice process with patients. The modified (TAM) model in his dissertation can be constructed by focusing on one critical success factor and study it deeply from different angels.

6.3 Implications for Practice

To understand the acceptance and adoption of artificial intelligence projects in health domain a modified (TAM) model was employed in this dissertation. The implications for researchers to have practical application to their AI health project by confirming the critical external factors based on their organizational culture and their process, ensuring the best practice application to guarantee project success. The consequences thereby, is to improve the attitude towards artificial intelligence projects for their business environment.

6.4 Limitations and future research

Current dissertation has certain limitations which may allow the presence of further studies to be conducted with respect of (TAM) and artificial intelligence projects. due to shortage in finding related research studies that discuss artificial intelligence projects in the health sector in the Gulf region, UAE mainly. Future studies must be extended widely in different countries and analyze the significance of presenting critical success factors for artificial intelligence projects in health sector. Also, having complicated procedures to interview doctors and health project managers in the government and private hospitals results in hesitating to meet them. Moreover, the findings of this study are only concidering the critical success factors that assist in implementing artificial intelligence project in the health sector in UAE and Dubai emirate mainly without pointing out the failure factors.

References

Abdullah, F. & Ward, R. (2016). Developing a general extended technology acceptance model for e-learning (GETAMEL) by analysing commonly used external factors. *Computers in Human Behavior*, vol. 56(2), pp.238-256.

Albu, A. & Stanciu, L. (2015*)*. In E-Health and Bioengineering Conference. *Cover Art: 5th Benefits of using artificial intelligence in medical predictions* [online]. University of Iaşi. Iaşi.19-21 November. IEEE Xplore Digital Library. [Accessed 15 Jan 2019]. Available at: https://ieeexplore.ieee.org/document/7391610

Aldosari, B., Al-Mansour, S., Aldosari, H. & Alanazi, A. (2018). Assessment of factors influencing nurses acceptance of electronic medical record in a Saudi Arabia hospital. Informatics in Medicine Unlocked. Elsevier Ltd, vol. 10(December 2017), pp. 82–88.

Al-Emran, M., & Salloum, S. A. (2017). Students' Attitudes Towards the Use of Mobile Technologies in e-Evaluation. International Journal of Interactive Mobile Technologies (IJIM), vol. 11(5), 195–202.

Alharbi, S., & Drew, S. (2014). Using the technology acceptance model in understanding academics' behavioural intention to use learning management systems. *International Journal of Advanced Computer Science and Applications*, vol. 5(1), 143-155.

Alloghani, M., Hussain, A., Al-Jumeily, D. & Abuelma'atti, O. (2015). Technology Acceptance Model for the Use of M-Health Services among health related users in UAE. *Cover Art: In Developments of E-Systems Engineering* [online]. University of Liverpool. Liverpool. 13-14 December. IEEE Xplore Digital Library. [Accessed 20 Jan 2019]. Available at: https://ieeexplore.ieee.org/document/7563640

Alrawashdeh, T. A., Firstauthor, A. B., & Secondcoauthor, D. E. (n.d.). Extended UTAUT to examine the acceptance of web based training system by public sector's employees.

Amer, N.T. (2016). *Factors Impacting the Adoption and Implementation of Business Intelligence and Analytics Projects in Organizations*. Doctoral dissertation. The British University in Dubai.

Baharom, F., Khorma, O.T., Mohd, H. & Bashayreh, M.G. (2011). Developing an extended technology acceptance model: doctors 'acceptance of electronic medical records in Jordan.

Baptista, G. & Oliveira, T. (2015). Understanding mobile banking: The unified theory of acceptance and use of technology combined with cultural moderators. *Computers in Human Behavior*, vol. 50(1), pp.418-430.

Basak, E., Gumussoy, C.A. & Calisir, F. (2015). Examining the factors affecting PDA acceptance among physicians: an extended technology acceptance model. *Journal of healthcare engineering*, vol. 6(3), pp.399-418.

Bennani, A.E. & Oumlil, R. (2014). IT acceptance by nurses in morocco: application of a modified unified theory of acceptance and use of technology. IBIMA Business Review, pp.1.

Bennani, A.E. & Oumlil, R. (2014). The Acceptance of ICT by Geriatricians reinforces the value of care for seniors in Morocco. IBIMA Publ. J. African Res. Bus. Technol. J. African Res. Bus. Technol.

Brannen, J. (2017). *Mixing methods: qualitative and quantitative research*. London U.K.: Routledge Publications.

Briz-Ponce, L. & García-Peñalvo, F.J. (2015). An empirical assessment of a technology acceptance model for apps in medical education. *Journal of medical systems*, vol. 39(11), pp.176.

Campbell, D. T., & Fiske, D. W. (1959). Convergent and discriminant validation by the multitrait-multimethod matrix. Psychological Bulletin, vol. 56(2), 81.

Charleonnan, A., Fufaung, T., Niyomwong, T., Chokchueypattanakit, W., Suwannawach, S. & Ninchawee, N. (2016). Predictive analytics for chronic kidney disease using machine learning techniques. *Cover Art: In Management and Innovation Technology International Conferenc*e [online]. University of Bang-San. Bang-San. 12-14 September. IEEE Xplore Digital Library. [Accessed 14 January 2019]. Available at: https://ieeexplore.ieee.org/abstract/document/8025242

Chen, D., Goyal, G., Go, R., Parikh, S. & Ngufor, C. (2018). Predicting Time to First Treatment in Chronic Lymphocytic Leukemia Using Machine Learning Survival and Classification Methods. *Cover Art: IEEE International Conference on Healthcare Informatics.* University of New York. New Work. 4-7 July. IEEE Xplore Digital Library. [Accessed 5 Feb 2019]. Available at: https://ieeexplore.ieee.org/abstract/document/8419409

Cheng, W. T., & Chen, C. (2015). The Impact of e-Learning on Workplace On-the-job Training. *International Journal of E-Education, e-Business, e-Management and e-Learning*, vol. 5(4), 212.

Chin, W. W. (1998). The partial least squares approach to structural equation modeling. *Modern Methods for Business Research*, vol. 295(2), 295–336.

Christensen, L.B.R., Thomas, G., Calleya, J. & Nielsen, U.D. (2018). The Effect of Operational Factors on Container Ship Fuel Performance. In Proceedings of Full Scale Ship Performance. The Royal Institution of Naval Architects.

Cohen, I.G., Amarasingham, R., Shah, A., Xie, B. & Lo, B. (2014). The legal and ethical concerns that arise from using complex predictive analytics in health care. Health affairs, 33(7), pp.1139-1147.

Costantino, F., Di Gravio, G. & Nonino, F. (2015). Project selection in project portfolio management: An artificial neural network model based on critical success factors. *International Journal of Project Management*, vol. 33(8), pp.1744-1754.

Creswell, J.W. & Creswell, J.D. (2017*). Research design: Qualitative, quantitative, and mixed methods approaches*. Sage publications.

Dahiya, D. and Mathew, S.K. (2016). IT assets, IT infrastructure performance and IT capability: a framework for e-government. Transforming Government: People, Process and Policy, 10(3), pp.411-433.

Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. MIS Quarterly, 319–340.

Dreheeb, A. E., Basir, N., & Fabil, N. (2016). Impact of System Quality on Users' Satisfaction in Continuation of the Use of e-Learning System. *International Journal of E-Education, e-Business, e-Management and e-Learning*, vol. 6(1), 13.

Emad, H., El-Bakry, H.M. & Asem, A. (2016). A Modified Technology Acceptance Model for Health Informatics.

Ertosun, M.G. & Rubin, D.L. (2015). Probabilistic visual search for masses within mammography images using deep learning. *Cover Art: In 2015 IEEE International Conference on Bioinformatics and Biomedicine* [online]. University of Washington. Washington. 9-12 November. IEEE Xplore Digital Library. [Accessed 10 February 2019]. Available at: https://ieeexplore.ieee.org/document/7359868

Fathema, N., Shannon, D. & Ross, M. (2015). Expanding the Technology Acceptance Model (TAM) to Examine Faculty Use of Learning Management Systems (LMSs) In Higher Education Institutions. *Journal of Online Learning & Teaching*, vol. 11(2).

Fayad, R. & Paper, D. (2015). The technology acceptance model e-commerce extension: a conceptual framework. Procedia Economics and Finance, 26(1), pp.1000-1006.

Fornell, C., & Larcker, D. F. (1981). Evaluating Structural Equation Models With Unobservable Variables and Measurement Error. Journal of Marketing Research, 18(1), 39–50. https://doi.org/10.2307/3151312

Fotin, S.V., Yin, Y., Haldankar, H., Hoffmeister, J.W. & Periaswamy, S. (2016). Detection of soft tissue densities from digital breast tomosynthesis: comparison of conventional and deep learning approaches. In Medical Imaging 2016: Computer-Aided Diagnosis, 9785(1), pp. 97850

Government.ae (2018). UAE Strategy for Artificial Intelligence. [online] Government.ae. Available at: https://government.ae/en/about-the-uae/strategies-initiatives-and-awards/federal-governments-strategies-and-plans/uae-strategy-for-artificial-intelligence [Accessed 27 Oct. 2018].

Hair Jr, J. F., Hult, G. T. M., Ringle, C., Sarstedt, M., Hair, J. F. F., Hult, G. T. M., … Sarstedt, M. (2016). *A primer on partial least squares structural equation modeling (PLS-SEM).* Sage Publications.

Harun, A., Liew, T. S., Kassim, A. W. M., & Sulong, R. S. (2015). Smartphone dependency and its impact on purchase behavior. Asian Social Science, 11(26), 196.

Helia, V.N., Asri, V.I., Kusrini, E. & Miranda, S. (2018). Modified technology acceptance model for hospital information system evaluation–a case study. *Cover Art: The 2nd International Conference on Engineering and Technology for Sustainable Development* [online]. University of Yogyakarta. In MATEC Web of Conferences. [Accessed 11 February 2019]. Available at: https://www.matec-conferences.org/articles/matecconf/abs/2018/13/matecconf_icet4sd2018_01101/matecconf_icet4sd2018_01101.html

Henseler, J., Ringle, C. M., & Sarstedt, M. (2015). A new criterion for assessing discriminant validity in variance-based structural equation modeling. *Journal of the Academy of Marketing Science*, vol. 43(1), 115–135.

IBM (2018). Watson Natural Language Understanding. [online] Ibm.com. Available at: https://www.ibm.com/cloud/watson-natural-language-understanding [Accessed 29 Oct. 2018].

IEEE Xplore Digital Library. (2016). *Cover Art: Customized web-based system for elderly people using elements of artificial intelligence* [online]. University of Košice. IEEE Xplore Digital Library. [Accessed 20 January 2019]. Available at: https://ieeexplore.ieee.org/document/7733252

Jordan, M.I. & Mitchell, T.M. (2015). Machine learning: Trends, perspectives, and prospects. Science, 349(6245), pp.255-260.

Kamat, P. (2016). Research ethics. Retrieved from https://www3.nd.edu/~pkamat/pdf/ethics.pdf

Khaleej Times. (2019). UAE Strategy for Artificial Intelligence to drive growth in the country. [online]. [Accessed 5 October 2018]. Available at: https://www.khaleejtimes.com/nation/dubai/artificial-intelligence-to-drive-uae-growth

Kline, R. B. (2011). Convergence of structural equation modeling and multilevel modeling. na.

Kok, J.N., Boers, E.J., Kosters, W.A., Van der Putten, P. & Poel, M. (2009). Artificial intelligence: definition, trends, techniques, and cases. Artificial intelligence, 1.

Kononenko, I. (2001). Machine learning for medical diagnosis: history, state of the art and perspective. *Artificial Intelligence in medicine*, vol. 23(1), pp.89-109.

Lawrence, D., Palacios-González, C. & Harris, J. (2016). Artificial Intelligence. Cambridge Quarterly of Healthcare Ethics, 25(02), pp.250-261..

Ma, W., & Yuen, A. (2011). 11. E-LEARNING SYSTEM ACCEPTANCE AND USAGE PATTERN. Technology Acceptance in Education: Research and Issues, 201.

Marangunić, N. & Granić, A. (2015). Technology acceptance model: a literature review from 1986 to 2013. Universal Access in the Information Society, 14(1), pp.81-95.

Maruping, L.M., Bala, H., Venkatesh, V. & Brown, S.A. (2017). Going beyond intention: Integrating behavioral expectation into the unified theory of acceptance and use of technology. *Journal of the Association for Information Science and Technology*, vol. 68(3), pp.623-637.

Mijwel, M.M. (2015). History of Artificial Intelligence. Computer science, college of science, pp.1-6.

Milošević, I., Živković, D., Manasijević, D., & Nikolić, D. (2015). The effects of the intended behavior of students in the use of M-learning. *Computers in Human Behavior*, vol. 51, 207–215.

Moen, H., Peltonen, L.M., Heimonen, J., Airola, A., Pahikkala, T., Salakoski, T. & Salanterä, S. (2016). Comparison of automatic summarisation methods for clinical free text notes. *Artificial intelligence in medicine*, vol. 67(1), pp.25-37.

Moher, D., Shamseer, L., Clarke, M., Ghersi, D., Liberati, A., Petticrew, M., Shekelle, P. & Stewart, L.A. (2015). Preferred reporting items for systematic review and meta-analysis protocols (PRISMA-P) 2015 statement. Systematic reviews, 4(1), pp.1.

Mokyr, J. (2018). The Past and the Future of Innovation: some lessons from Economic History. Explorations in Economic History.

Muk, A. & Chung, C. (2015). Applying the technology acceptance model in a two-country study of SMS advertising. *Journal of Business Research*, vol. 68(1), pp.1-6.

Nadri, H., Rahimi, B., Afshar, H.L., Samadbeik, M. & Garavand, A. (2018). Factors Affecting Acceptance of Hospital Information Systems Based on Extended Technology Acceptance Model: A Case Study in Three Paraclinical Departments. Applied clinical informatics, 9(02), pp.238-247.

Najafabadi, M.M., Villanustre, F., Khoshgoftaar, T.M., Seliya, N., Wald, R. & Muharemagic, E. (2015). Deep learning applications and challenges in big data analytics. *Journal of Big Data*, vol. 2(1), pp.1.

Nardi, P.M. (2018). Doing survey research: A guide to quantitative methods. Routledge.

Navimipour, N.J. & Soltani, Z. (2016). The impact of cost, technology acceptance and employees' satisfaction on the effectiveness of the electronic customer relationship management systems. *Computers in Human Behavior*, vol. 55(1), pp.1052-1066.

Nibali, A., He, Z. & Wollersheim, D. (2017). Pulmonary nodule classification with deep residual networks. *International journal of computer assisted radiology and surgery*, vol. 12(10), pp.1799-1808.

Nithya, B. & Ilango, V. (2017). Predictive analytics in health care using machine learning tools and techniques. *Cover Art: In Intelligent Computing and Control Systems (ICICCS)* [online]. University of Madurai. Madurai. 15-16 June. IEEE Xplore Digital Library. [Accessed 6 February 2019]. Available at: https://ieeexplore.ieee.org/abstract/document/8250771

Panicacci, S., Donati, M., Fanucci, L., Bellin, I., Profili, F. & Francesconi, P. (2018). Population Health Management Exploiting Machine Learning Algorithms to Identify High-Risk Patients. In 2018 IEEE 31st International Symposium on Computer-Based Medical Systems (CBMS), pp. 298-303.

Phatthana, W. & Mat, N.K.N. (2011). The Application of Technology Acceptance Model (TAM) on health tourism e-purchase intention predictors in Thailand. *Cover Art: In 2010 International Conference on Business and Economics Research* [online]. University of Kedah. International Proceedings of Economics Development and Research. [Accessed 7 February 2019]. Available at: http://www.ipedr.com/vol1/43-B10046.pdf

Price, W.N. (2017). Artificial Intelligence in Health Care: Applications and Legal Implications

Punnoose, A.C. (2012). Determinants of intention to use eLearning based on the technology acceptance model. *Journal of Information Technology Education: Research*, vol. 11(1), pp.301-337.

Rajamhoana, S.P., Devi, C.A., Umamaheswari, K., Kiruba, R., Karunya, K. & Deepika, R. (2018). Analysis of Neural Networks Based Heart Disease Prediction System. *Cover Art: In 2018 11th International Conference on Human System Interaction (HSI)* [online]. University of Gdansk. Gdansk. 2-4 July. IEEE Xplore Digital Library. [Accessed 10 February 2019]. Available at: https://ieeexplore.ieee.org/document/8431153

Ringle, C. M., Wende, S., & Will, A. (2005). SmartPLS 2.0 (Beta). Hamburg. Available in Http://Www. Smartpls. De.

Safdari, R., Saeedi, M.G., Valinejadi, A., Bouraghi, H. & Shahnavazi, H. (2017). Technology Acceptance Model in health care centers of Iran. *International Journal of Computer Science and Network Security (IJCSNS)*, vol. 17(1), p.42.

Salloum, S. A. S., & Shaalan, K. (2018). Investigating students' acceptance of E-learning system in Higher Educational Environments in the UAE: Applying the Extended Technology Acceptance Model (TAM). The British University in Dubai.

Salloum, S. A., & Shaalan, K. (2018). Adoption of E-Book for University Students. In International Conference on Advanced Intelligent Systems and Informatics (pp. 481–494). Springer.

Salloum, S. A., Al-Emran, M., Shaalan, K., & Tarhini, A. (2018). Factors affecting the E-learning acceptance: A case study from UAE. Education and Information Technologies, 1–22.

Salloum, S.A.S. (2018). Investigating students' acceptance of e-learning system in higher educational environments in the UAE: Applying the extended technology acceptance model (TAM).

San, A.N.C. & Yee, C.J. (2013). The Modified Technology Acceptance Model for Private Clinical Physicians: A Case Study in Malaysia, Penang. *International Journal of Academic Research in Business and Social Sciences*, vol. 3(2), p.380.

Senapathi, M., & Srinivasan, A. (2014). An empirical investigation of the factors affecting agile usage. In Proceedings of the 18th international conference on evaluation and assessment in software engineering (p. 10). ACM.

Shaikhina, T. & Khovanova, N.A. (2017). Handling limited datasets with neural networks in medical applications: A small-data approach. *Artificial intelligence in medicine*, vol. 75(2), pp.51-63.

Shukla, S., Lakhmani, A. & Agarwal, A.K. (2016). Approaches of artificial intelligence in biomedical image processing: A leading tool between computer vision & biological vision. *Cover Art: In Advances in Computing, Communication, & Automation (ICACCA)(Spring), International Conference* [online]. University of Dehradun. Dehradun. 8-9 April. IEEE Xplore Digital Library. [Accessed 9 February 2019]. Available at: https://ieeexplore.ieee.org/document/7578900

Solano-Lorente, M., Martínez-Caro, E. & Cegarra-Navarro, J.G. (2013). Designing a Framework to Develop eLoyalty for Online Healthcare Services. *Electronic Journal of Knowledge Management*, vol. 11(1).

Strudwick, G. (2015). Predicting nurses' use of healthcare technology using the technology acceptance model: an integrative review. *CIN: Computers, Informatics, Nursing*, vol. 33(5), pp.189-198.

Swarup, P. (2012). Artificial Intelligence. *International Journal of Computing and Corporate Research*, vol. 2(4).

Teeroovengadum, V., Heeraman, N. & Jugurnath, B. (2017). Examining the Antecedents of ICT Adoption in Education Using an Extended Technology Acceptance Model (TAM). *International Journal of Education and Development using Information and Communication Technology*, vol. 13(3), pp.4-23.

Teo, T. S. H., Srivastava, S. C., & Jiang, L. (2008). Trust and electronic government success: An empirical study. *Journal of Management Information Systems*, vol. 25(3), 99–132.

The DHA launches Innovation and Artificial Intelligence strategy [online]. [Accessed 27 October 2018]. Available at: https://www.dha.gov.ae/en/DHANews/Pages/DHANews5931652-14-05-2018.aspx

Tongco, M.D.C. (2007). Purposive sampling as a tool for informant selection. Ethnobotany Research and applications, 5(1), pp.147-158.

ValueStrat. (2018). *How can Artificial intelligence transform the healthcare sector in UAE* [online]. [Accessed 27 October 2018]. Available at: https://valustrat.com/can-ai-transform-healthcare-sector-uae

Vemulapalli, V., Qu, J., Garren, J.M., Rodrigues, L.O., Kiebish, M.A., Sarangarajan, R., Narain, N.R. & Akmaev, V.R. (2016). Non-obvious correlations to disease management unraveled by Bayesian artificial intelligence analyses of CMS data. *Artificial intelligence in medicine*, vol. 74(1), pp.1-8.

Venkatesh, V., Thong, J.Y. & Xu, X. (2016). Unified theory of acceptance and use of technology: A synthesis and the road ahead.

Visitdubai.com (2018). AI & Robotics in Medicine - Dubai's New Healthcare Strategy. [online] Visitdubai.com. Available at: https://www.visitdubai.com/en/business-in-dubai/why-dubai/news-and-insights/artificial-intelligence-in-healthcare [Accessed 27 Oct. 2018].

Wallis, L., Hasselberg, M., Barkman, C., Bogoch, I., Broomhead, S., Dumont, G., Groenewald, J., Lundin, J., Norell Bergendahl, J., Nyasulu, P. & Olofsson, M. (2017). A roadmap for the implementation of mHealth innovations for image-based diagnostic support in clinical and public-health settings: a focus on front-line health workers and health-system organizations. Global health action, 10(3), pp.1340254.

Wangpipatwong, S., Chutimaskul, W. & Papasratorn, B. (2008). Understanding Citizen's Continuance Intention to Use e-Government Website: a Composite View of Technology Acceptance Model and Computer Self-Efficacy. *Electronic Journal of e-Government*, vol. 6(1).

Who, X. (2011). Extending TAM: Success factors of Mobile Marketing. *American Academic & Scholarly Research Journal*, vol. 1(1), pp.1-5.

Wong, K. K.-K. (2013). Partial least squares structural equation modeling (PLS-SEM) techniques using SmartPLS. Marketing Bulletin, 24(1), 1–32.

Yamada, Y. & Kobayashi, M. (2018). Detecting mental fatigue from eye-tracking data gathered while watching video: Evaluation in younger and older adults. *Artificial intelligence in medicine*, vol. 91 (2018): 39-48.

Zare, S. (2017). Identifying and Prioritizing Supply Chain Management Strategic Factors Based on Integrated BSC-AHP Approach.

Zhang, Q., Zhou, D. & Zeng, X. (2017). Hear the heart: Daily cardiac health monitoring using Ear-ECG and machine learning. *Cover Art: In Ubiquitous Computing, Electronics and Mobile Communication Conference (UEMCON)* [online]. University of New York. New York. 19-21 October. IEEE Xplore Digital Library. [Accessed 9 February 2019]. Available at: https://ieeexplore.ieee.org/document/8249110

Zhao, J., Zhang, M., Zhou, Z., Chu, J. & Cao, F. (2017). Automatic detection and classification of leukocytes using convolutional neural networks. *Medical & biological engineering & computing*, vol. 55(8), pp.1287-1301.

Ziuziański, P., Furmankiewicz, M. & Sołtysik-Piorunkiewicz, A. (2014). E-health artificial intelligence system implementation: case study of knowledge management dashboard of epidemiological data in Poland. *International Journal of Biology and Biomedical Engineering*, vol. 8(1), pp.164-171.

Appendix A: Questionnaires / Employees Survey

Success Factors of Implementing Artificial Intelligence (AI) Projects in Health Sector in Dubai Questionnaire

My name is Shaikha Alhashmi and I'm currently doing my Master's Dissertation. The purpose of this questionnaire is to understand the main reasons behind the critical success factors that enable the development of "AI" projects in the Health sector.

This survey will take 5-10 minutes.

Part one: Demographic information

1- What is your gender?
- Female
- Male

2- What is your age group?
- 18-29
- 30-39
- 40-49
- 50-59
- 60+

3- What is your Education level?
- High school graduate, diploma
- Bachelor's Degree
- Master's Degree
- Doctorate Degree
- Other

4- In which sector do you work?
- Government
- Semi-Government
- Private
- Private indivisual business

5- What is your profession?
- Doctor
- Information Technology
- Project Management
- Business

6- If you are working in the IT domain, what is your role?
- IT Professional

- IT Engineer
- IT Support
- IT Manager
- IT Project Leader/Manager
- IT Supervisor

7- What best describes your role in the organization?

- Junior level
- Senior//professional level
- Managerial level
- Higher mangemnet

8- Your experience in years:

- 0-3 years
- 0-7 years
- 10+ years

9- Do you think AI projects will increase the healthcare performance levels in Dubai?

- Yes
- No
- Not sure

10- From your experience, select the most relevant factors of implementing a successful AI Project

- Managerial
- Operational
- Strategic
- IT Infrastructure
- organizational

11- Based on your opinion, is there a difference between IT and AI Projects?

- Yes
- No
- Not sure

12- Please describe the difference:

13- Please specify in what areas the IT projects differs than AI projects?

- Operational
- Cost
- Testing
- Quality
- Advantage
- Performance

Part two: Managerial Factor

1- Do you think that Governance affects the AI Project Success?

- Strongly Agree
- Agree
- Neutral
- Disagree
- Strongly Disagree

2- Do you think that teamwork affect the AI Project Success?

- Strongly Agree
- Agree
- Neutral
- Disagree
- Strongly Disagree

3- Do you think that availability of financial resources (Government Support) affect the AI Project Success?

- Strongly Agree
- Agree
- Neutral
- Disagree
- Strongly Disagree

Part Three: Operational Factor

1- Do you think that the high complexity of the AI system/solution affects the AI Project Success?

- Strongly Agree
- Agree
- Neutral
- Disagree
- Strongly Disagree

2- Do you think that the health information accuracy in AI system/solution affects the AI Project Success?

- Strongly Agree
- Agree
- Neutral
- Disagree
- Strongly Disagree

Part Four: Strategic Factor

1- Do you think that having clear strategic goals affect the AI Project Success?

- Strongly Agree
- Agree
- Neutral
- Disagree
- Strongly Disagree

2- Do you think that having long term planning by the organization affect the AI Project Success?

- Strongly Agree
- Agree
- Neutral
- Disagree
- Strongly Disagree

Part Five: Information Technology Infrastructure Factor

1- Do you think that allocating proper resources affect the AI Project Success?

- Strongly Agree
- Agree
- Neutral
- Disagree
- Strongly Disagree

2-Do you think that simplicity of AI Design (user-friendly) affect the AI Project Success?

- Strongly Agree
- Agree
- Neutral
- Disagree
- Strongly Disagree

3- Do you think that system quality (performs as the desired functions) affect the AI Project Success?

- Strongly Agree
- Agree
- Neutral
- Disagree
- Strongly Disagree

4- Do you think that content/information quality affect the AI Project Success?

- Strongly Agree
- Agree

- Neutral
- Disagree
- Strongly Disagree

Part Six: Organizational Factor

1- Do you think that the organizational culture contributes to AI Project Success?

- Strongly Agree
- Agree
- Neutral
- Disagree
- Strongly Disagree

2- Do you think that having proper training for the employees contribute to AI Project Success?

- Strongly Agree
- Agree
- Neutral
- Disagree
- Strongly Disagree

3- Do you think that having local expertise in AI projects contribute to AI Project Success?

- Strongly Agree
- Agree
- Neutral
- Disagree
- Strongly Disagree

4- Do you think that having an international partnership with AI leading companies contribute to AI Project Success?

- Strongly Agree
- Agree
- Neutral
- Disagree
- Strongly Disagree