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Study of the Continuous Intention to use Artificial Intelligence Based Internet of Medical Things (IoMT) During Concurrent Diffusion

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Study of the Continuous Intention to use Artificial Intelligence Based Internet of Medical Things (IoMT) During Concurrent Diffusion

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Abstract

Fatema Saleh Aldhaen

The Influence Diffusion of Innovation Factors Has as Determinants of Continuous Intention to Use Ai-Based IoMT

Keywords: Internet of medical things (IoMT), Continuous intention, Diffusion of innovation, Artificial intelligence, Healthcare, and Bahrain.

This research was about the continuous intention of healthcare professionals to use internet of medical things (IoMT) embedded with artificial intelligence (AI). IoMT and AI are evolving innovations and diffusing at the same time. It was not known in what way the two complex technologies diffusing concurrently could influence continuous intention to use IoMT. In addition, behavioural aspects namely motivation and training to use IoMT have been argued to intervene in the relationship between an AI based IoMT and continuous intention to use IoMT. Diffusion of Innovation theory was applied to explain the relationship between diffusion factors that aid the diffusion of AI based IoMT and continuous intention to use IoMT. The five factors relative advantage, compatibility, complexity, observability and trialability were chosen as determinants of continuous intention to use IoMT using DoI theory. Self-determination theory and theory of planned behaviour were used to introduce the interventions in the relationship between diffusion factors and continuous intention to use IoMT. UTAUT was used to explain the influence of the moderators artificial intelligence awareness, novelty seeking behaviour and age of healthcare professionals. The central issue investigated was the determinants of continuous intention of healthcare professionals to use IoMT with behavioural attributes of motivation and training conceived as mediators of the relationship between diffusion factors and continuous intention to use IoMT in the presence of moderators.

Quantitative research methodology was used to test the research model developed to understand the relationship between the five diffusion of innovation theory factors and continuous intention to use IoMT when AI based IoMT is still diffusing. The concurrent diffusion of two new technologies was investigated using a research model that was developed for studying the healthcare professionals and their intention. The research was conducted in Bahrain in the healthcare sector. A sample of 354 healthcare professionals participated in the research. Structural equation modelling was used to analyse the data and test the hypothesis.

The research showed that healthcare professionals will continue to use concurrently diffusing technologies depending on the relative advantage, complexity and compatibility of the innovations that diffuse. In addition, the results show that healthcare professionals will be motivated by the compatibility of AI-based IoMT if they have to continuously use IoMT. Furthermore, training enables both the organization and the healthcare professionals to overcome dilemma in case they have to continue to use an innovation during its diffusion or when new innovation surface in the market. Finally, artificial intelligence awareness is able to moderate the relationship between relative advantage, complexity and training to use IoMT. Thus, this research contributes to the discipline of behavioural intention of healthcare professionals in determining the influence of an artificial intelligence based IoMT on continuous intention to use IoMT when artificial intelligence embedded in IoMT diffuses concurrently with IoMT. Where IoMT diffusion factors can be used as a determine of continuous intention to use IoMT, artificial intelligence could be understood as a moderator of the relationship between diffusion factors and training to use IoMT, thus demonstrating the combined diffusion of the two technologies diffusing concurrently.

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The completion of this research has allowed me to develop a better understanding of academic writing and research processes, as well as learn useful new knowledge that will improve Bahrain's health sector. This project's academic experiences have allowed me to develop professionally and personally. I am grateful for these gifts of knowledge.

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Dedication

I would like to dedicate this study to my mother, God father prof. Abdulla Al-Hawaj, sisters, brother-in-law, who have been incredibly supportive throughout this journey. The completion of this study demonstrates that anyone can achieve anything if they put in the effort. Failures should not discourage you; they are indicators that will assist you in achieving your goals.

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List of Abbreviation

Abbreviation	Term
AI	Artificial intelligence
AMOS	Analysis of Moment Structures
AVE	Average Variance Extracted
CFA	Confirmatory Factor Analysis
CFI	Comparative Fit index
DF	Degree of Freedom
DOI	Diffusion of Innovation
ECT	Expectation Confirmation Theory
GFI	Goodness Fit Index
IoMT	Internet of Medical Things
IFI	Incremental Fit Index
IoT	Internet of things
IoWT	Internet of Wearable things
IS	Information System
IT	Information Technology
NFI	Normed Fit Index
RMR	Root Mean Residual
RMR	Root Mean square residual
RMSEA	Root Mean Square Error of Approximation
SDT	Self Determination Theory
SEM	Structural Equation Modelling
TAM	Technology Acceptance Model
TLI	Tucker–Lewis Index
TPB	Theory of Planned Behaviour
TRA	Theory of Reasoned Action
TTF	Task Technology Fit
UTAUT	Unified Theory of Acceptance and Use of Technology

1. Chapter 1: Introduction

1.1. Introduction

Determination of continuous usage of new technology or an innovation has been a topic of research during the last few decades e.g., (Rabaai et al., 2021; Kao et al., 2019; de Boer et al., 2019). Determination of the continuous intention to use IoMT as innovation, when IoMT is still diffusing is a major area of research recently (Kang, 2019). In an era where new technological inventions and innovations are being developed rapidly, there has been a constant question on whether users will accept those inventions and innovations and use them continuously. For instance, the Internet of Medical Things (IoMT) as innovation is rapidly changing the way technology can be used to support people in the field of healthcare (Baudier et al. 2019; Haughey et al, 2018) but the continuous intention of healthcare professionals to use IoMT is still not a well-understood topic (Ahmad et al., 2020; Al-Momani et al., 2018; Zhang et al., 2015. Some argue (e.g., Kim & Kim, 2016) that IoMT will be accepted while others say that it has limitations and hence usage and acceptance of IoMT could be a question mark (Al-Garadi, 2018). IoMT is still in its early stages of growth and only a few studies have dealt with the issues of end-user adoption and acceptance of IoMT (Tűrkeș et al., 2020). In addition, another innovation namely artificial intelligence (AI) is now being embedded in IoMT (Venkatesh, 2019) making IoMT a complex technology, which implies that simultaneously another technology is diffusing alongside IoMT. The concurrent or simultaneous diffusion of two new technologies is another challenge that affects the adoption of or continuous intention to use technology as this aspect has not been well investigated by researchers and has the potential to discourage users from continuously using technology (Rossman et al., 2008). This argument applies to the artificial intelligence based IoMT and is a gap in the literature.

1.2. Background

IoT, a recent innovation, is promising to change the lives of many individuals in terms of enabling those individuals to make informed decisions and reduce the cost of accessing services (Perwej et al., 2019; Kagita et al., 2020). IoMT is a derivative of IoT (Liu et al., 2021; Giri et al., 2019). However, IoT is considered to be a complex and abstract technology leading to doubts about its utility to people, the reason being the interaction between devices is complex as the number of IoT devices is increasing steadily and requiring less human intervention (Zhou et al., 2018). Further, IoT involves smart devices connected to the network producing huge volumes of data that require new ways to gather and collect that data (Van Deursen & Mossberger, 2018). These challenges could distance the users from adopting and using IoT depriving them of the benefits that could accrue if IoT was used. Thus, the intention to use and sustain such use of innovation like IoT becomes a concern.

With a constantly changing technology that is complex, using the latest devices including those considered as part of IoMT is becoming complicated leading to challenges in making the healthcare management system more efficient. So many times, users will try out certain innovations but, in the end, may discard the innovation, indicating that the innovation needs to withstand trials. For instance, Greenhalgh (2017) found out that in Norway, less than 1% of the hospitals used telehealth for outpatient consultation, a type of IoMT, despite there being a policy to use telehealth and 75% of the hospitals having accepted to use telehealth. Similarly, Maskeliūnas et al. (2019) argue motivation is another factor that could either motivate or demotivate people, for instance, older people may not be motivated if they do not perceive any added value (de Souza & Baldanza, 2018; Melenhorst et al., 2006). Furthermore, researchers are still coming to terms with the various challenges that are being encountered by users, right from the innovation stage to the usage stage of it. Taylor et al. (2018) point out that in their survey conducted on health professionals 71% felt that care providers and clinicians are not ready to utilise the data collected using the medical devices that are connected. This points out the challenge of lack of training on the part of healthcare providers and clinicians.

In another example, Maresova et al. (2020) pointed out that medical regulations are another challenge that needs to be overcome by innovative organisations failing which the innovations may not be brought out for common use and benefit of users. Mignon (2016) while arguing and linking innovation to diffusion, points out that innovation can be related to drivers, challenges, and strategies/policies which will either drive usage of IoMT or block its usage. Mignon argues that drivers could be incentives to users and people who are interested in innovation. A brief about diffusion is provided next

1.2.1. Diffusion

The significance of new technologies is derived from their widespread adoption across a wide range of users and applications as well as geographical locations. For sustainable growth, the spread of technological innovations among manufacturers both domestically and abroad is essential (Stokey, 2021).

The definition of the term "diffusion" is determined by the characteristics of the diffusion processes, including what they are, how they work, and why valuable medical advances do not spread more quickly (Dearing & Cox, 2018).

Rogers (1995) developed the "diffusion of innovation" theory for the spread of innovations across people and organisations after combining evidence from over 508 diffusion studies (Lai, 2017). Where diffusion was defined as "a dynamic process in which an innovation is communicated over time among the members of a social system through certain channels", where diffusion is determined through four main elements of the diffusion of innovations are innovation, communication channels, time, and social system.

Another important aspect of diffusion of innovation is the importance of embedded technology like AI. Such innovations have an additional driver in the form of a second innovation diffusing concurrently with the first innovation. This research studies the case of AI as an innovation that is concurrently diffusing with IoMT. A brief about AI is given next.

1.2.2. Artificial intelligence

The term artificial intelligence (AI) refers to a contemporary technique based on computer science that creates programs and algorithms to make machines clever and effective for carrying out tasks that typically need competent human intellect (Manickam et al., 2022). Also, (Bohr& Memarzadeh,2020) explained that AI is about utilising human intelligence in machines through technological advancements.

The health sector is being transformed by various forms of AI both individually and collectively in order to cut costs and improve patient care (Forbes Insights Team 2019). In practical term, AI mimics or demonstrate a certain feature of human intelligence or intelligent behaviour, such as learning, thinking, or problem-solving.

According to (Chen & Decary, 2020) AI is not just one type of technology but rather a broad category of intelligent activities and actions produced by computer models and algorithms. The parts that follow will examine and analyse the appropriate use of existing AI technology in healthcare. Recent advances in AI, particularly in machine learning (ML), deep learning (DL), Natural Language Processing (NLP), fuzzy logic, and speech recognition are only a few of the subsets of AI that have special abilities and functions that can enhance the performance of modern medical sciences (Manickam et al., 2022). AI is now the most important component in imitating human tasks in industries like healthcare, business, environmental control, and other fields (Lloret et al., 2016). It handles the responsibilities that previously could only be handled by human intellect (Mahalakshmi & Latha, 2019). Consequently, those intelligent technologies make it easier for humans to participate in clinical diagnosis, medical imaging, and decision-making which holds great promise for having a significant impact in the healthcare industry (Forbes Insights Team 2019).

The current Internet of Medical Things (IoMT) and AI technology combined to improve the quality of care that patients receive at home remotely from successful smart living environments (Elbagoury et al., 2021). Moreover, it is projected that the development of AI will have an effect on how healthcare professionals operate, especially those who interface with digital data, such as radiologists or pathologists, due to the possibility for considerable automation (Chen et al. 2021; Davenport and Kalakota 2019).

According to Song et al. (2020) that the combination of both IoT sensors and AI offers a broad range of intellectual transmission and strong processing capabilities for healthcare professionals during the pandemic of Covid 19. Modern research has revolutionised wireless communication and sensor technology by creating tiny wearable and implantable sensors. The healthcare system has undergone a complete transformation as a result of the decision-making abilities of combined IoMT and AI.

Point of care (POC) devices such as ultrasound, thermometers, glucometers, and ECG readers come with Internet connectivity and cloud storage facilities that let users track the sensing devices have demonstrated that they assist in data archiving and analysis when combined with IoT and AI (Kaushik et al., 2020). Additionally, (Manickam et al.,2020) indicated that AI-based systems are also tailoring the most efficient course of therapy for people, along with specific drugs such as Wearable health tracker devices make it simple to monitor and give health services information on patients' heart rates and activity levels. AI-based solutions are used to process the massive amount of data coming from numerous sources and identify anomalies for specific people. Also, smartwatches and wristbands, which are commercial IoMT fitness monitoring solutions, have recently drawn more attention because of their combined sensing and wireless data transfer capabilities (Ding et al., 2018).

Through the use of medical devices, IoMT technology links patients and physicians, enabling remote access for the collection, processing, and transmission of medical data across a secured network. By enabling wireless health monitoring, IoMT technologies help reduce unnecessary hospital stays and related health expenses.

The following section provides a distinction between artificial intelligence IoT and non-artificial intelligence on IoT devices.

1.2.3. Artificial intelligence based IoT

The integration of AI with IoMt offers numerous benefits, including the capacity for systems to autonomously learn from data and make decisions without human intervention (Khan et al, 2021). So, IoMT devices collect, transmit, and analyse data, and healthcare professionals must verify the analyses; however, with the help of AI, the integrated device can make intelligent decisions without consulting a doctor.

IoMT-based AI devices can continuously monitor people's health, especially for elderly and disabled people who can they receive the assistance through the intelligent robotics, smart homes, and virtual assistants (Al-Turjman et al., 2020). Moreover, AI can be used to detect network intrusions and intermediary security threats on IoMT systems, among other security-related tasks (Mohamed Shakeel et al.,2018; Javaid et al, 2016) Using IoT-based AI which can be helpful for accurate and speedy diagnosis of any ailments. The knowledge is also essential and crucial for stopping the disease's spread and saving lives. (Awotunde et al, 2022). A diagnosis based on chest radiography pictures may benefit from the use of AI. When it comes to diagnosing many human-specific diseases, AI is capable of becoming just as accurate as humans. It implies that it can reduce the amount of time that doctors spend making an illness diagnosis. It is also quicker than a human and performs the diagnostic at a lower standard than a doctor or radiologist (Awotunde et al, 2022).

During Covid 19 pandemic the use of IoT based AI at the front lines of clinical practice had been significantly advancing the development of contemporary intelligent medical care, including remote screening, intelligent diagnosis, and remote intensive care (Chen et al., 2019). Examples as the following: -

Remote screening: Remote screening eliminates the need for extensive crowd-screening in emergency departments, lowering the risk of virus exposure (Chen et al., 2019). The issue of manual reading of image scanning reports being too slow and inaccurate can be resolved with the use of intelligent diagnostics. Front-line doctors can use the intelligent diagnosis as an additional tool to swiftly evaluate whether patients have COVID-19 infection (Chen et al., 2019).

Drones: Drones are increasingly being used for delivery, spraying disinfectants, and remote monitoring of polluted areas, as we have seen during the pandemic. Drones may also gain popularity after COVID-19 for a variety of jobs like sanitizing expansive compounds, outside hospital locations, and others. It helps carry medications to contaminated areas, which lessens the workload for the medical staff. Additionally, it hastens the distribution of medical necessities including blood, vaccines, and emergency injections (Soni, 2020)***.*** Drones can be used for remote surveillance of infectious areas and hospital locations. Any discrepancies in this region can be reported by the camera's AI capability. A drone with an attached camera aids ambulances by reducing traffic along the way (Soni, 2020). These numerous IoT-equipped linked drones gather and submit a variety of data to cloud platforms for additional analysis and decision-making (Soni, 2020).

Wearable Technology: One of the most extensive applications of AI and IoT in technology is this. End users can wear devices on their wrists, arms, or legs that automatically track vital statistics such as heartbeat, blood pressure, number of steps taken, and many others. Better clarity on health conditions will be offered because the data is recorded in real-time. For example, smart Watches for Depression constructed by IoT based on AI that can measure depression levels. This tool can monitor depression and offer suggestions for treatment. This cutting-edge application of IoT and AI in healthcare aids in determining users' levels of depression. data will be collected and transmitted through IoT, and the level of depression will be analysed by AI (Rajput, 2020).

1.2.4. Non-artificial intelligence based IoT

IoMT plays as a facilitator between patients and doctors, where doctors can give their patients great diagnoses and care (Henze, 2021). Both parties will be satisfied as a result, and communication with the treating physician is also easier (Henze, 2021), where sensors are embedded in medical devices to monitor patient's health and transmit the collected data through a network so that patients can interact with their healthcare professionals (Vishnu et al., 2020).

Most medical devices connect to the internet and are viewed by healthcare professionals. These solutions make medical care more affordable and provide quicker access. It is a network of wireless, connected, and interconnected electronic devices that can gather, transmit, and store data over a network without requiring human-to-human or human-to-computer interaction (Kelly et al, 2020). IoMT has shown promise in connecting a wide range of medical devices, sensors, and healthcare experts in order to provide top-notch medical services in remote areas (Issa & Thabit, 2022; Dwivedi et al, 2021). Many IoT applications and devices are available in the market. These technologies have made a significant contribution to duties like patient monitoring, keeping in touch with healthcare professionals, enhancing the effectiveness of rehabilitation, etc. (Yuehong et al., 2016).

Examples fitness bands, smartwatches and smart glasses, glucose monitoring, connected inhalers, Ingestible IoMT sensors, IoMT-connected contact lenses and portable heart rate monitoring (York, 2021).

If innovation adopters feel that there is a relative advantage and compatibility to using new technology then the innovation will diffuse (Lyytinen and Damsgaard, 2001; Peltier et al., 2012; Henard and Szymanski, 2001; Moore and Benbasat,1991; Zhang et al., 2015). For instance, healthcare providers could suggest wearables to patients if those wearables have a relative advantage over manual measurements and have compatibility with the computer network, then the caregivers will suggest patients use wearables and the innovation will diffuse. Similarly, strategies may be needed to enable the devices to be connected to the network to be efficient to handle the signals. In another instance the failure of innovation in the system is not always blamed on the adopters, but rather on factors such as the diffusion process within the social system, compatibility of technology, and the fact that adopters do not adopt and use technology in the same way throughout the innovation process (Dintoe, 2019; Dintoe, 2018; Jacobsen, 1998). Furthermore, affordability is yet another factor that could either encourage diffusion or block the usage of innovation (Taylor et al., 2018).

The above examples demonstrate that usage of IoMT devices or the lack of them has thus become an important topic of discussion in the healthcare industry that is constantly looking to improve patient care, especially with multiple technological innovations coming out in rapid succession (Arora et al., 2020; Joyia et al., 2017). IoMT's usage has become an important concern for researchers and healthcare professionals alike (De Michele & Furini, 2019). Particularly where technological innovations related to medical devices are still diffusing there is a state of flux in understanding the sustainability of the usage of those devices. If technological innovations concerning devices like medical and medical monitoring devices, clinical wearables and remote sensors are to be used to improve the efficiency of the healthcare management system (Javaid & Khan, 2020; Zeadally et al., 2019), then using such technologies should be simple, easy to operate, easy to understand its purpose (Al-Eidan et al., 2018), training is available to operate the device, the device and the backup support motivate users (Matta & Pant, 2019). Also believing in innovation and having adequate training to support the faith of the users in the innovation would assist in the adoption and diffusion of the innovation process (Valente & Davis, 1999).

Literature shows that barriers affect the continuous usage of IoMT by healthcare professionals in supporting patients and such barriers need to be removed if IoMT usage has to be improved. According to the literature, barriers to the usage of IoT and therefore

IoMT, include illiteracy on the part of the user related to technology, failure of technology not well managed and high level of training (Nijeweme – d'Hollosy et al. 2015). Other barriers include lack of awareness and knowledge (Hovenga & Grain, 2022; Brous et al., 2020), behavioural challenges (Tsourela & Nerantzaki, 2020; Al-Momani et al., 2018), security and privacy (Kelly et al., 2020; Tawalbeh et al., 2020; Padyab et al., 2019), the duality of technology (Brous et al., 2020), lack of qualified workforce (Brous et al., 2020; Luthra et al., 2018) and employee resistance (Hajiheydari et al., 2021; Muhsen et al., 2021).

Literature shows that barriers affect the continuous usage of IoMT by healthcare professionals in supporting patients and such barriers need to be removed if IoMT usage has to be improved. According to the literature, barriers to the usage of IoT and therefore IoMT, include illiteracy on the part of the user related to technology, failure of technology not well managed and high level of training (Nijeweme – d'Hollosy et al., 2015). This implies that continuous intention to use IoMT could suffer if the IoMT technology is complex to use or requires a high level of training to use or if it requires to be managed to enable smooth operation when dealing with complex data acquisition processes. Other barriers that have been identified in the literature include:

- Lack of awareness and knowledge (Hovenga & Grain, 2022; Brous et al., 2020) - this highlights the need for the users of IoMT to be aware of the operations and have knowledge about the uses of the latest and advanced technologies embedded in IoMT. For instance, lack of awareness of the use of Artificial Intelligence in IoMT could deprive the users of the innovative operation of IoMT and its advantages.
- Behavioural challenges (Tsourela & Nerantzaki, 2020; Al-Momani et al., 2018) - this barrier could lead to users avoiding and ignoring IoMT as those users might be demotivated by some of the features of the IoMT devices including incompatibility and lack of relative advantage of the IoMT devices.
- Security and privacy (Kelly et al., 2020; Tawalbeh et al.,2020; Padyab et al. 2019) - this could be a major challenge that could discourage from users continuously using IoMT. For instance, if IoMT devices do not have built-in mechanisms to protect patient data, there could violations regarding the security and privacy issues as well as data protection. Such problems could expose the patients to risks of potential misuse of data.

- Duality of technology (Brous et al., 2020) - this implies that IoMT could be considered by users for its adoption as well as its impact on organisations. For instance, IoMT could be used for providing the best healthcare to patients while its impact on the organisation providing healthcare could lead to risky situations like security and privacy issues.
- Lack of qualified workforce (Brous et al., 2020; Luthra et al.,2018) - any advanced technology requires support from expert technicians to operate and put to use that technology. IoMT is no different as a lack of expert manpower could hinder the use and continuous use of IoMT.
- Employee resistance (Hajiheydari et al., 2021; Muhsen et al., 2021)- this could be a major factor in the continuous intention to use IoMT as employees could feel that the technology used is difficult to understand and operate. For instance, there are many interoperability problems associated with IoMT when devices from different companies are used in a single healthcare setting. In such situation's employees could find it difficult to use the devices and could show resistance to continuously using the devices.

Amongst the above, behavioural challenges of both the healthcare professionals and patients in using the IoMT could further be divided into more factors like lack of motivation to use IoMT, deficiency in meeting end-user needs and lack of contribution with the end-user insights and experiences of using IoT (Padyab et al. 2019). The use of IoMT by both patients and patient care providers, therefore, is not an automatic occurrence. In fact, in the literature studies concerning behavioural intention to use IoMT or IoT have been found. However, the study of the process of using IoT, as a corollary IoMT, is lacking (Lu et al., 2018). It is further seen in the literature that there is a lack of understanding of the beneficiaries' and experts' perspectives regarding IoT and hence IoMT as an innovation and its usage at the level of the end-user as an individual is a challenge (Padyab et al., 2019). Further to gaining an understanding of the background and usage of IoMT from different perspectives, the next section describes the problem that affects the diffusion of IoMT and its influence on the continuous intention to use IoMT.

1.3. Problem statement

Technological innovations like IoMT bring along with them new challenges to users including large volumes of data, complex and abstract technology leading to doubts on its utility to people, automatic decision-making, lower visibility, greater ambiguity and amplified security and privacy risks (Koutras et al., 2020; Mawgoud et al., 2019). These challenges are further amplified when another innovation like AI affects or is associated with IoMT, which could marginalise many from deriving benefits of innovations like IoMT making it necessary to investigate how the marginalised could be helped (Price, 2019). Since the focus of this research is AI-based IoMT, the marginalised could be understood as those who have to use IoMT but find it difficult to adopt it or continuously use it, for instance, healthcare professionals. This situation could lead to a digital divide and inequality (Pivoto et al., 2019). This divide and inequality could affect the marginalised from deriving benefits offered by AI-based IoMT. Usage and non-usage of IoMT thus have become an important concern of researchers, professionals, policymakers, and service providers.

This problem has serious implications for healthcare professionals, patients, and policymakers. IoT is referred to in the healthcare sector as the internet of medical things (IoMT). For instance, for healthcare professionals could be faced with large volumes of data about patients which could be difficult to analyse and understand leading to difficulties in providing the best healthcare. Decision making on the quality of healthcare could be complex. Similarly, when two innovations are offered together with one embedded in another (e.g., embedding artificial intelligence in IoMT) could lead to a lack of understanding of the simultaneous use of the two technologies for patient care leading to marginalising the patients. This could happen if a healthcare professional fails to exploit the advantages provided by the two technologies to ensure that the best healthcare is provided to the patient. Yet again it can be seen that advanced technologies used in IoMT could create a digital divide amongst healthcare professionals working in an organisation, leading to policymakers to be in a dilemma on whether to use and reuse an advanced IoMT or not. Such are the problems that could surface in the continuous intention to use IoMT. To overcome this problem of lack of knowledge on whether AI-based IoMT will be continuously used or not by healthcare professionals, in particular, researchers have been studying a few factors to gain knowledge on how those factors could cause the digital divide and inequality (Honeyman, 2020). In addition to what extent those factors could be manipulated to reduce the digital divide and inequality amongst the marginalised leading to increased chances of usage and continuous intention to use IoMT also assumes importance (Friemel, 2016).

Furthermore, from the literature, it has been observed that IoMT as a technology is still diffusing across the healthcare sector (Costigan & Lindstrom, 2016). However, it is not clear whether this diffusion will lead to usage of IoMT by healthcare professionals as diffusion of innovation like IoMT need not necessarily lead to usage and reduce digital divide or inequalities. However, some factors have been identified in the literature as either hindering or facilitating the successful usage and repeated usage of IoMT with diffusion as the main independent phenomenon that affects the usage of IoMT. Leading factors of diffusion that have been identified in the literature as representing and causing the innovation to diffuse are relative advantage, complexity, compatibility, observability and trialability (Emani et al., 2018). There are contradictory arguments that indicate that these factors may or may not influence the usage of innovation like IoMT or need additional strategies (Kamin, 2017). Further, research shows that successful diffusion of innovation that leads to usage of IoMT could be facilitated by certain intervening factors including training in IoMT (Abdullah & Ward, 2016) and motivation to use IoMT (Baudier et al., 2019) although no research outcome has comprehensively established their role in the relationship between diffusion of IoMT factors and continuous intention to use IoMT. Finally, it is also pointed out that moderators like AI, novelty-seeking behaviour and age can affect the diffusion of AI-based IoMT and there is a need to know whether and to what extent these moderators affect the diffusion of IoMT and continuous intention of healthcare professionals to use IoMT (Sima et al., 2020; Baccarella et al., 2020; Venkatesh et al. 2012). These gaps cause problems for both patients and healthcare professionals in providing the best healthcare to the patients and the marginalised.

1.4. Research gaps

The central concern of this research is to understand the relationship between the DOI factors and continuous intention to use AI-based IoMT and see how to determine and improve the continuous usage of IoMT when both the innovations namely AI and IoMT are concurrently diffusing. AI and IoMT are both evolving technologies and are still diffusing amongst the population who want to use them (Greco et al., 2020; Mavrogiorgou et al., 2019). Although there are several challenges for IoMT to diffuse and users to use IoMT this research has identified only a few of them. The challenges considered were the complexity of technology (Sarkar, 2020; Ghosh et al., 2018), the need for training (Amiot, 2015), need for motivation to use IoMT (Newman et al., 2019; Chaghari et al., 2017), need to provide maintenance support for IoMT devices (Otaibi, 2019) and above all need to manage a constantly changing technology. DOI has been argued to provide a theoretical base to understand how the various challenges concerning relative advantage, compatibility, complexity, observability and trialability (DOI factors) affect continuous intention to use IoMT (Putteeraj et al., 2021; Daragmeh et al., 2021; Baudier et al. 2019). However, studies that have used IoMT as well as AI as innovations that are still diffusing, to determine the usage or continuous intention to use IoMT, are far from few and there is a lack of clarity on how and to what extent diffusion of innovation as a concept can enable the determination of the continuous intention to use IoMT (Bloom et al., 2021). Especially when one confronts a situation where diffusion of innovation (DOI) as a theory has not been tested to explain the concurrent diffusion of two innovations the gap existing in the literature becomes complex to address (Lin, 2021; Rossman et al., 2008). Literature shows that despite advantages, IoMT usage by both patients and healthcare providers is not improving (Hartono et al., 2021; Saarikko et al., 2020). Lack of knowledge on how to improve the usage level of IoMT amongst both healthcare professionals and patients is a major gap in the literature (Dai et al., 2020; Gatouillat et al., 2018). This statement is supported by Emani et al. (2019) and Salleh & Daud (2019) who recommend further investigations to be conducted to understand the usage of IoT in areas like healthcare to gain knowledge on how to improve continuous intention to use IoMT. These research gaps have been succinctly transformed into the following research questions.

RQ1: *What factors determine the continuous intention of healthcare professionals to use AI-based IoMT that is still diffusing?*

RQ2: *Do mediators and moderators affect the relationship between determinants of the continuous intention of healthcare professionals to use AI-based IoMT and the continuous intention of healthcare professionals to use AI-based IoMT during diffusion of AI base IoMT?*

RQ3: *Which of those mediators and moderators enable the determinants to influence continuous intention of healthcare professionals to use AI-based IoMT during diffusion of AI base IoMT?*

The scope of this research is thus reduced to:

- to investigate the construct of continuous intention to use IoMT in the context of healthcare professionals.
- to study and determine the extent to which the diffusion of innovation components affects continuous intention to use IoMT.
- to identify whether there are interventions that influence the relationship between the components concerning the diffusion of innovation and continuous intention to use.
- to study and determine the extent of influence of the interventions on the relationship between the components concerning the diffusion of innovation and continuous intention to use.

1.5. Research Aim and Objectives

This research aims to examine the determination of the continuous intention to use IoMT of healthcare professionals when IoMT embedded with another technology namely artificial intelligence is still diffusing. The research aim will be achieved using the following objectives:

- By examining the current literature on factors influencing continuous intention to use IoMT with built-in artificial intelligence during its diffusion. (RQ1)

- By determining the relationship between the various factors identified as affecting continuous intention to use IoMT and continuous intention to use IoMT and develop appropriate hypotheses. (RQ1 & RQ2)
- By developing the methodological framework for the research (RQ3)
- By evaluating the various relationships through statistical analysis and testing the hypotheses using the findings derived from the analysis. (RQ2 & RQ3)
- By evaluating the findings with relevant literature and cross-checking whether the research questions have been answered. (RQ1, RQ2 and RQ3)
- By demonstrating that the research has made contributions to knowledge, theory and practice, and bridging the identified gaps in the literature. (RQ1, RQ2 and RQ3)

1.6. Proposed Methodology

This research aims to answer the research questions that involve the terms 'what' and 'to what extent'. These terms point toward the need to use objective ways to deal with the questions. Methodology literature posits that any research question that needs to answer objectively usually uses explanatory research which in turn uses a quantitative research method (Saunders et al., 2019). Thus, this research has developed a research model that needs to be used to examine the central issue of continuous intention to use IoMT. DOI factors have been used as the determinants of the continuous intention to use IoMT and the role of two intervening factors has been examined for their influence on the relationship between DOI factors. Similar research methods have been used by other researchers who have developed conceptual models and tested the intention to use IoMT using quantitative research methods (e.g., Al-Rahmi et al., 2019; Baudier et al., 2019).

1.7. Significance of this Research

The literature review shows that there is a major concern in the health care sector related to the low level of use of IoMT concerning its reflection in the patient care. Although several research outcomes have been produced in this area from managerial and technical perspective but the point of view of the decline in the healthcare in the large countries such as England and the United States, it appears that there is a gap in the literature about lack of knowledge on how to reverse this decline by improving the usage of IoMT. This gap calls for fresh investigations to understand how to improve the usage levels of IoMT in the healthcare industry and provide better patient care. The outcome of this research is expected to fill this gap by developing a conceptual model involving continuous intention to use IoMT, diffusion of innovation factors (relative advantage, compatibility, complexity, observability and trialability), and motivation to use IoMT and training in IoMT. Knowledge generated through this research is expected to contribute to the body of knowledge related to the usage of IoMT.

1.8. The originality of the research

Both IoMT and AI are found to be evolving innovations and diffusing at the same time. It is not known in what way an innovation like IoMT that is still diffusing could influence continuous intention to use IoMT. The originality lies in the investigation of the influence of DOI factors as determinants of continuous intention to use IoMT and the role of mediators and moderators in that relationship.

1.9. Research Outline

This doctoral thesis is developed into the following sections:

- **Chapter 2 Literature Review**

This chapter provides an extensive review of the literature concerning the healthcare sector and IoMT, relevant theories and gaps found in the literature.

- **Chapter 3 Theoretical framework**

This chapter describes the conceptual framework developed to address the gaps identified in the literature review and presents the hypotheses formulated to test the research model.

- **Chapter 4 Research Methodology**

This chapter provides a complete explanation of the choice of the research methodology and data analysis techniques adopted.

- **Chapter 5 Data analysis**

This chapter analyses the data collected and tests the hypotheses for their acceptance or falsification. In addition, provides the findings derived through the data analysis.

- **Chapter 6 Discussion**

This chapter discusses the findings derived from the data analysis and uses them to answer the research questions and identifies the significance of the findings.

- **Chapter 7 Conclusion**

This chapter provides conclusions of this research which includes achievement of the aim and objectives, contribution to knowledge, theory, methodology and practice. In addition, it identifies the limitations of this research and suggests areas for future research.

2. Chapter 2: Literature Review

2.1 Introduction

This chapter reviews the literature concerning continuous intention to use the internet of medical things (IoMT) and its determination when IoMT is still diffusing. The chapter also reviews relevant theories that concern with IoMT diffusion and its continuous usage. Determination involves understanding the relationships that could exist between diffusion of IoMT and continuous intention to use IoMT by healthcare professionals. Hence determination of continuous intention to use IoMT dwells on behavioural attributes of users who are healthcare professionals, which could intervene in the relationship between IoMT diffusion and the continuous intention to use IoMT of healthcare professionals. A comprehensive review of the literature concerning the concept of IoMT is provided in this chapter which is based on the findings of the various studies and the gaps identified thereof. To begin with, this chapter appraises the context of the healthcare sector, the current IoMT scenario, the healthcare professionals who intend to use IoMT and examples of IoMT. Next, the review proceeds with the argument that IoMT is an evolving technology (Wolken et al., 2018, Malik et al., 2017) followed by a critical review of the continuous intention to use IoMT. The evolution of IoMT is translated to the diffusion of IoMT and reviewed. Its relationship to the endpoint of diffusion namely continuous intention to use IoMT has been analysed. Various theories can explain the phenomena of IoMT, its diffusion to continuous intention to use and the behavioural attributes of the healthcare professionals including motivation to use IoMT, training to use IoMT, novelty-seeking behaviour to use IoMT, age and artificial intelligence (AI) awareness have been reviewed. A section has been devoted to describing the gaps that exist in the literature. The conclusions of this chapter provide the basis for drawing the theoretical framework discussed in the next chapter.

2.1.1. Brief on the process of reviewing the literature

Performing a literature review involved searching for academic, scientific, and peer-reviewed articles, books, and conference proceedings using keywords like "diffusion," "internet of things," "adoption of technological instruments in healthcare," and "artificial intelligence in healthcare." The search was performed using the truncation symbols, ADD, and OR Boolean operators. Search terms included m-health, Internet of Things (IoT), Internet of Medical Things (IoMT), Telemedicine, Continuous Intention to Use, Intention to use, adoption of technology, innovation adoption, diffusion of innovation, diffusion theory, behavioural theory, motivation and training, artificial intelligence, technology diffusion, novelty seeking, adoption theories, demographic variables, methodology related terms like research philosophies, data analysis, data collection, structural equation modelling and many others.

An online search for various academic material was carried out utilising search engines including Google Scholar and Google. In addition, the University of Bradford enabled access to digital libraries including Pro Quest and EBSCO. During the search, many terms including m-health and wearable devices acceptance, adoption, and intention to use were found to be the most repetitively used terms in studies in healthcare in context patients. The themes that emerged included diffusion of innovation theory, components of diffusion of innovation theories, internet of medical things, continuous intention to use, artificial intelligence, motivation, training, novelty seeking, structural equation modelling and philosophies related to methodologies. The review heavily relied upon two recently published papers (Baudier et al., 2019; Al-Rahimi et al., 2019) in addition to the diffusion of recurrent innovations (lim, 2021).

2.2. Status of Healthcare Sector

The healthcare sector is growing fast. Modern healthcare is complex, specialised, costly and heavily dependent on technology (Barić, 2020; Shahid et al., 2019). Healthcare management has become even more complex with the growing healthcare needs of the people and the many challenges that are generated by the environment surrounding them. For instance, Bloom et al. (2018) highlights that growth in the health sector causes economic strain on countries. In addition, healthcare needs are constantly growing and are expected to continue to grow (Barić, 2020). One of the important aspects of the growing healthcare needs and the challenges faced by hospitals is the dependence of those hospitals on technological advances that take place. For instance, Appendix 1 provides examples of telemedicine, a form of IoMT, that supports hospitals (Qureshi & Krishnan, 2018; Emon et al., 2018). Telemedicine is a technology-based concept applied in the healthcare sector increasingly (Rawat, 2018). This is reviewed in the next section.

The above discussion highlights the current status of the healthcare sector which is growing and bringing alongside challenges that are also growing. There is a need to understand and address those challenges. Some of the serious challenges that need to be considered are the growing population of the elderly and special needs (Nasr et al., 2020; Chen et al., 2020), complex technologies (Barić, 2020; Brous et al., 2020), limited availability of financial resources (Končar et al., 2020; Safarani et al., 2018), untrained practitioners and staff to use new technologies (Končar et al., 2020; Yaacoub et al., 2020), cost of installation and implantation and development of digital devices (Brous et al., 2020; Končar et al., 2020; Harris et al., 2015; Yazici, 2014), digitisation of health services (Vaagan et al., 2021). Amongst these challenges currently, the challenge created by digital transformation is very significant as it is revolutionising the healthcare landscape (Rosalia et al., 2020; Weinelt, 2016). New and novel concepts are being introduced into the market in quick succession. This gives very little time for the individuals, professionals, systems and decision-makers to adapt to those new concepts and ideas. There is also the challenge of the burden of understanding and developing appropriate behaviours concerning these new technologies and possibilities (European Commission, 2018). Thus, behavioural aspects related to the usage of new technologies gain currency. Considering the importance given to healthcare by various governments to protect the lives of their citizens, there is a need to address the challenge of digital transformation and its usage (Lee & Lee, 2020; Cheung et al., 2019; To et al., 2019). One such technological innovation that is promising to help overcome the challenges associated with digital transformation and is expected to support governments in reducing the cost of providing good healthcare is IoMT. IoMT can be broadly brought under the umbrella term telemedicine (Dai et al., 2020). Thus, before discussing the various aspects of IoMT it is useful to discuss telemedicine as the concept of telemedicine could provide the basis on which IoMT is grounded.

2.3. Telemedicine in healthcare

The technology of telemedicine is not new but has been continuously evolving. A brief history given below provides an idea of its evolution, use and challenges. Telemedicine was first introduced in the 1900s for example electrocardiographic data, was transmitted via a telephone cable. Similarly, television technology is another example of telemedicine (Vladzymyrskyy et al., 2016; Patterson, 2005). Nebraska Psychiatric Institute used a television link between the institute itself and Norfolk for conducting educational and training (Emon et al., 2018; Zundel, 1996). Following the advent of the mobile phone and the widespread use of the internet, telemedicine became further popular (Rothberg & Martinez, 2020; Gao et al., 2020). Changing technology and the latest innovations are accelerating healthcare advancement in telemedicine (Meaghann et al., 2020; Khairat et al., 2019). Since the first appearance of health informatics in the 1950s and 1960s (Stenlund & Mines, 2012; Collen, 1986), it was possible to easily collect information that could be saved, retrieved and shared by numerous healthcare professionals to improve the quality of delivery of patients care (Rubí et al., 2020; O'Connell, 2015). These arguments are also applicable to derivatives of telemedicine. In the current research, one such derivative that will be studied is the IoMT which is a technology that has been derived from the more generic internet of things (IoT). Thus, to gain an in-depth knowledge about IoMT it was necessary to know about IoT. This is discussed next.

2.4. The era of the Internet of Things

According to the literature IoT is defined as a connected network of billions of physical objects through the Internet to collect and share data globally based on certain protocols (Ray, 2016; Madakam et al., 2015), to accomplish smart and safe reorganisation, locating, online tracking and real-time monitoring systems. For example, home and medical appliances, smartphones and cameras could be connected through IoT regardless of the type or the size of those devices to remotely use them (Vermesan & Friess, 2014). IoT is not only used to collect, share or track data (Alferidah & Jhanjhi,

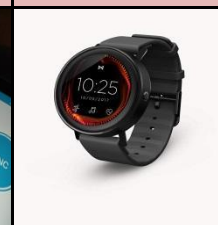
2020) but Zhao and Ge (2013) explained that it could be used to sense data also. Zhao and Ge (2013) further explained that the IoT alludes to different technologies and devices that sense data, for example, gas inductors, laser scanners, infrared sensors, GPS (Global Position System) and RFID.

As far as the utility of IoT, literature shows that despite the advantages that have been associated with IoT there are serious limitations that could hinder its continuous usage by professionals in different sectors that need to be addressed if those advantages of IoT are to be exploited. For instance, limitations of IoT includes user security and privacy concerns, user resistance, lack of user motivation, the difficulty faced by users to continuously use IoT due to rapidly changing technology, cost of changing IoT sensors, complexity in using IoT (built-in advanced technology like AI), interoperability problems, ever-increasing volume of data to be handled by IoT, lower acceptance of IoT, advancing technology not fully diffused, lack of training facilities to operate IoT. These limitations can reduce the acceptance level and continuous usage of IoT (Elkhodr et al., 2016; Kim et al., 2016; Karlov et al., 2019; Lee & Shin, 2019; Tawalbeh et al., 2020; Tűrkeș et al., 2020; Nižetić, 2020; Talwar et al., 2020). This introduction to IoT provides the basis to discuss and review the concept of IoMT which is the focus of this research. Thus, the following section provides a critical review of IoMT.

2.5. Internet of Medical Things in Healthcare

As a result of the quick-paced and continuous advancements that are taking place in the domain of IoT, it is essential to comprehend some of the key terminologies that are utilised by engineers as well as the industry (Qureshi & Krishnan, 2018). Since wearable devices became a significant part of the technology world and were exposed to people first, subsequently the terminology of the Internet of Wearable Things (IoWT) emerged. Such devices were worn by users and were used as monitoring, tracking system or as motion sensors. IoWT combined the utility of wearable devices and IoT systems (Joyia, et al., 2017). The wearables derived a fundamental advantage from the IoT, and it can be seen that they have now entered everyone's lives in areas including entertainment, fashion and health (Trawick & Yeung, 2019; Wright & Keith, 2014). Examples of some of the IoMT devices are provided in table 2-1.

Table 2-1: Examples of IoMT devices (Mavrogiorgou et al. 2019).

IoMT devices	**Fitbit Aria Wi-Fi Smart Scale**	**iHealth Sense**	**Withings Pulse O2**	**iHealth Track**	**Misfit Vapor.**
					
	(Spear, 2020)	(Anats, 2022)	(Vernet, 2017))	(Stafferton, 2017)	(Muguna, 2022)
	Mi Body Composition Scale	**Fitbit Alta HR**	**Mi Electric Toothbrush**	**Garmin Vivofit**	**Withings Steel HR**
					
	(Rcgeeks, 2020)	(FitRated Editorial Team, 2020)	(Grinvalds, 2021)	(Henke, 2020)	(WURM, 2020)

2.6. Review of IoMT literature

2.6.1. Current trends in IoMT

IoMT is a technology which is still evolving and therefore diffusing continuously into the market (Greco et al., 2020; Mavrogiorgou et al., 2019). The diffusion is progressing at a fast rate and many innovations are being brought out into the market in quick succession. For instance, Maia et al. (2014) developed a platform of EcoHealth platform to share real-time data between both the doctor and the patients. The primary aim of the platform was to ensure improvement in the health monitoring and medical checkups of the patients, thus making the operation energy-efficient and timesaving. The IoMT is categorized into many enabling technologies. Some of the examples of the current trends in the field of IoMT include remote patient morning, wearable devices for the IoMT solution, telehealth, and a software platform for smartphones.

Recently, many applications have been created and developed that are proposed to bring mobile-based facilities to the patients. The smartphone applications enable the patients to know about their diseases after the analysis in the fields of gynaecology and paediatrics. Appendix 2 shows a list of IoMT devices and their descriptions with their designated jobs. This table provides an idea about the trends taking place in the sphere of IoMT which is an example of the diffusion of IoMT.

2.6.2. Advantages and challenges in using IoMT

- **Advantages**

The primary advantage of IoMT is the provision of medical treatments at home complying with the hospital standards. Further, it also makes the healthcare service provision efficient as per patients' needs (Karahoca et al., 2018). Other benefits found include sensing and visualisation of the design of the system as an essential way to improve healthcare and reduce cost (Hassanalieragh et al., 2015). Other benefits identified in the literature include analysing the problems like heart rate, monitoring ECG and oxygen saturation in the blood (Rodrigues et al., 2018;), energy efficiency, saving in time and cost-effectiveness (Singh, 2016).

- **Challenges**

Matar et al. (2016) argued that challenges are associated with IoMT, including the problems and issues of hardware implementation and design optimisation related to

IoMT. Other challenging issues in IoT enabled healthcare include an array of complicating factors. For instance, the lack of availability of cost-effective and accurate smart medical sensors, unstandardised IoT based system architectures, the heterogeneity of connected wearable devices, the multi-dimensionality and high volume of generated data and the high demand for interoperability (Meinert et al., 2018). It is also seen that the concept of IoMT is multidisciplinary and combines knowledge from the different fields including engineering, computer science, behavioural science, decision science, and many other applied areas in the field of medicine and public health (Meinert et al., 2018). This implies that many challenges could occur due to the differences that exist across various disciplines that make the operation of IoMT difficult due to compatibility problems that may arise when two different disciplines are brought together to achieve a common purpose. Another important challenge is that IoMT is still diffusing into the healthcare market and more and more innovations are being brought out frequently. Additionally, Rubí and Gondim (2019) argued that without unified, consistent, and interoperable schemes, the adoption and implementation of IoMT would be drastically hampered.

2.6.3. The concept of Continuous Intention to use IoMT

Medical sector is one of the sectors that is exploiting new technology to the betterment of patient care. Medical and medical monitoring devices, clinical wearables and remote sensors are some of the topics currently being researched as these devices are known to contribute to improving the healthcare of patients (Uddin & Syed-Abdul, 2020; Yetisen et al., 2018). Improving the efficiency of healthcare using the latest technology is expected to contribute to better systems, as well as population and patient outcomes (Horstmeier, 2015). An efficient health management system needs to answer how to systematically improve healthcare outcomes of a population of patients, one patient at a time, over a long term that is sustainable and repeatable (Mavrogiorgou et al. 2019; Horstmeier, 2015).

2.6.4. Determination of Continuous Intention to use IoMT and the gaps in the literature

From the above discussion it can be seen that the concept of IoMT is complex and involves both technology and behavioural aspect of users which have been described by researchers as an evolving technology that requires deeper investigation to understand (Gatouillat et al., 2018; Taylor et al., 2018). For instance, the combination of IoMT and artificial intelligence technologies increases the complexity of IoMT for the users thereby introducing a dilemma in minds of users about accepting and continuously using IoMT for the betterment of healthcare of patients (Sarkar, 2020; Ghosh et al., 2018). On the one hand, the technology is promising to revolutionise the healthcare sector while on the other acceptance and continuous use of IoMT is becoming a challenge for healthcare professionals (Sung et al., 2020; Valanarasu, 2019; Joyia et al., 2017). In the absence of a mechanism to enhance the user acceptance and the continuance intention to use IoMT (Kelly et al., 2020; Lee & Lee, 2020). It becomes difficult for both manufacturers of IoMT and healthcare professionals alongside the administrators of man healthcare organisations to implement IoMT and determine the behavioural attributes of healthcare professionals (Umair et al., 2021; Lederman et al., 2021; Chakraborty et al, 2019; Prayoga & Abraham, 2016). Therefore, a more detailed understanding of IoMT becomes necessary to develop and implement a conceptual model that could help in a better understanding and determination of the continuous intention to use IoMT.

To know why an understanding or determining the repeated usage of IoMT is a difficult aspect, the following analysis of the IoMT device has been provided as an example. Out of the devices provided in table 2-2, one example was taken to demonstrate the complexity involved in understanding the usage and continuous intention to use the IoMT. Fitbit Aria (Fitbit, 2020) is an IoMT tracking device and is a fitness wristband that is used in calculating the basal metabolic rate (BMR), which helps determine the estimated calorie expenditure of a person. This device needs to be used in sync with a tracking device like a mobile or a computer (Fitbit, 2020). Its technology requires the understanding of how to set it up, connect it to the tracking device, check the accuracy of the readings, computer or mobile logging aspects, battery issues, syncing tracker data to the Fitbit account in the tracking device, back up service problems, software problems and hardware issues. If one has to use such a device, then the complexity of using such a device could be a major barrier for users. Usage of such an IoMT device becomes difficult to understand and determine Alshamrani (2021) and Zeadally et al. (2019). This example demonstrates why repeated usage of IoMT is a major area of concern. From the above, it is possible to infer that the behavioural phenomenon of continuous intention to use IoMT embedded with another new technology, is not easy to understand and depends on the technology behind the device and also to what extent support services are available (Rodrigues et al., 2018). To know more about this aspect of the behavioural phenomenon of continuous intention to use IoMT the next section reviews the literature critically.

2.6.5. Behavioural aspects concerning the Continuous Intention to use IoMT

The discussions so far have talked about the many aspects concerning IoMT and the focus of this research which is the usage of or continuous usage intention of IoMT. Taking into account the various limitations of using IoMT and problems that are faced by users due to those limitations it is possible to argue that such limitations can impact the continuous intention to use IoMT. However, the literature is silent on how to determine and improve the usage of IoMT (Dai et al., 2020; Gatouillat et al., 2018) as well as continuous intention to use IoMT and what factors can contribute to it (Ahmad et al., 2020). In this section, some of the behavioural aspects that could affect continuous intention to use IoMT and have been discussed in the extant literature have been critically reviewed using the example of the support services that need to be provided to adopters of IoMT.

The importance of support services can be seen in table 2-2.

Table 2-2: Examples of support services provided to IoMT with brief description

#	Service	Product	Description
1	Ambient assisted living	Be Close Remote Monitoring system	Supports both the caregiver and the patient by providing comfort and independence Yilmaz (2019).
2	Health solutions using smartphones	iOximeter (app)	Used as an oximeter with smartphone Adrienn (2017).
3	Remote healthcare monitoring	Early Sense All-in-one	This is related to a person who has requirements related to measurements concerning the heart like heart rate, fall prevention, respiratory rate, early detection of patient deterioration and pressure ulcer prevention The National Institute for Health and Care Excellence (2016).

The examples of IoMT provided in table 2-2 indicate that usage of IoMT may require appropriate knowledge, competence, and additional equipment for instance network. Such networking of IoMT enhance the healthcare support to the patients but at the same time can be difficult for implementation by those professionals. This in turn may require healthcare professionals to be educated and trained to apprise them of the various features, standards and operational skills required to employ those IoMT devices. In such situations motivating healthcare professionals could be a challenging task and is not straightforward because those devices may have complex technology built-in that make their implementation, usage, acceptance and understanding by healthcare professionals difficult (Newman et al., 2019; Chaghari et al., 2017). This may entail a tedious training process and overcoming resistance to use through motivation. In addition to training the caregiver, continuous backup support must be given to ensure both the usage and functioning of the machine are as per the specifications of the device (Amiot, 2015). It is possible to imagine that providing training in such a situation could be a challenge as it depends on several factors about the trainer as well as the trained and any error in using the device could be life-threatening.

From the above, it is clear that using an IoMT is a major concern as it depends on complex technology and gaining knowledge on how to use it continuously. How to address this concern is a major challenge. Although there have been many models that have tried to determine and determine the continuous usage of IoMT or the behavioural intention of users of IoMT, such models have limitations. Literature shows that researchers have found conflicting user behaviour about technology usage and both satisfied and dissatisfied user experiences have been observed (Dehghani et al., 2016; Johnson et al., 2008). These arguments show that in the field of medical care, in particular, user behaviour regarding accepting a medical and medical monitoring device or any other IoMT device could be varying due to a variety of reasons including limitations of technology or user attributes. This varying usage behaviour is thus not easy to understand and determine and it appears many factors could be attributed to this while knowledge about those aspects appear to be incomplete in the literature (Baudier et al., 2019; Al-Rahmi et al., 2019). Further investigations are therefore required to bring out more comprehensive knowledge about those aspects that concern the usage of or continuous intention to use IoMT.

2.6.6. Factors that affect usage of IoMT

- **Diffusion Factors**

There are several factors that have been studied in the literature to understand the continuous intention to use IoMT. Literature shows that any innovation like IoMT begins with the process of diffusion through its life cycle (Rogers, 2003). Diffusion of innovation is a major concept that has been widely used by researcher to understand the adoption rate of innovation by the end-users (Putteeraj et al., 2021; Daragmeh et al., 2021; Shiau et al., 2018; Burgess et al., 2017; Zhang et al., 2015). As mentioned earlier that IoMT is an innovation that is still diffusing. Taking into account the utility and applicability of DoI for this research, five factors of innovation diffusion namely relative advantage, compatibility, complexity, observability and trialability become the main focus and are conceived as the determinants of the continuous intention of healthcare professionals to use IoMT. In addition to this, some researchers (e.g., Baudier et al., 2019; Lee et al., 2005; Van der Heijen, 2004; Venkatesh et al., 2002) have argued that motivation is an important aspect of the usage of technology or intention to use technology or behavioural intention to use IoMT. It is argued that a better understanding of the motivation of people concerned with usage or behavioural intention to use IoMT could be useful in improving the usage or behavioural intention to use IoMT, knowledge about which needs further clarity in the literature (Baudier et al., 2019). This is an important gap in the literature that if addressed is expected to bring in new knowledge on how to motivate users to use IoMT and enhance the continuous intention to use IoMT for the betterment of patients care. Similarly, another factor that was considered essential to this research was training in IoMT. It was found in the literature that training could be considered an inseparable part of using IoMT and an associate factor of motivation of users (Ozkeser, 2019).

- **Concurrent Diffusion of IoMT and Associated Technology**

In this research, the focus is on the continuous intention of healthcare professionals to use IoMT because this variable is argued to be a major concern in the literature relevant to the diffusion of IoMT (Lee & Kim, 2021; Al-Maroof et al., 2021). This implies that the core issue of research is identified as the continuous intention to use IoMT of healthcare professionals as a behavioural attribute. Thus, the following sections review the literature relevant to those factors including diffusion factors and behavioural factors, that need to be considered as part of the determination of the continuous intention to use IoMT of healthcare professionals when IoMT is still diffusing. Such factors are reviewed for their operationalisation as independent, mediating, and dependent variables. In addition, the review also takes into account certain moderating factors that make the situation more complex and identified gaps in the literature. Particularly when another advancing technology, for instance, artificial intelligence is embedded into IoMT then it becomes more complex to determine the behavioural attribute of healthcare professionals as two different technologies are diffusing concurrently. The spreading of multiple technological advances and their measurement using a single framework has caused problems for researchers (Bloom et al., 2021). Concurrent diffusion causes an environment that is difficult to describe for the users. In such a situation it is important to understand the role the second technology plays and determine the influence the two technologies have on behavioural attributes of the healthcare professionals who want to continuously use IoMT (Rossman et al., 2008). To understand the above, the following sections, review the relevant literature on factors that impact the diffusion of IoMT alongside an embedded technology and determine the continuous intention of a healthcare professional to use IoMT. The focus of this research, therefore, shifts to the behavioural aspects of healthcare professionals and theories concerning those aspects.

- **Behavioural Factors**

Furthermore, IoMT involves complex technologies for instance AI embedded in IoMT and understanding how to use IoMT over the long term requires the support of technicians who have to build the skills to use IoMT through training (Osifeko, 2020; Tang and Xia, 2016). However, literature shows there is a lack of knowledge on how training in IoMT as a concept has to be understood concerning the use of technologies and new technologies

(Gaynor et al., 2015; Al-Gahtani, 2016), especially concerning a diffusing technology. To what extent motivation and its associated concept training in IoMT affect continuous intention to use IoMT when it is diffusing is not well understood in the literature as hardly any research publication addressing this aspect has been found (Baudier et al., 2019).

- **Other Factors**

Literature shows that while discussing the relationship between usage of technology or diffusing technology on the one hand and factors influencing usage of technology or technology adoption behaviour on the other, additional factors need to be considered that moderate that relationship (Merhi et al., 2019; Chang et al., 2019; Venkatesh et al., 2012). For instance, one of the widely used theories that explain the importance of moderators in investigations related to technology usage behaviour is the UTAUT. Moderators like age, gender and experience were identified by Venkatesh et al. (2012) as moderating relationships between determinants of behavioural intention and use behaviour of technology. One of the determinants of continuous intention to use identified in the literature is hedonic motivation (Venkatesh et al., 2012). Other researchers have used different determinants including system learnability (representing user training) (Binyamin, 2019; Zaharias, 2009).

It must be noted here that the use of moderators has been widely recommended in the literature, yet in many investigations, the use of moderators makes those investigations complex leading to the non-inclusion of moderators (Merhi et al., 2019). This leaves a gap in the literature as such investigations remain inconclusive. Especially regarding investigations involving internet use and novelty seeking, researchers have recommended the use of moderators (Babić-Hodović & Arslanagić-Kalajdžić, 2019). These arguments indicate that in the current investigation on the continuous intention to use IoMT certain moderators can be introduced. Considering the fact continuous intention to use IoMT involves users of different age groups, age becomes an automatic moderator as literature shows that age as a factor produces different behavioural intentions amongst users (Martins et al., 2018). Age as a moderating factor in this research, therefore, gains currency.

Further, IoMT is a fairly new concept and is considered a novel idea (Rodrigues et al., 2018). Literature shows that the perceived behaviour of users of new or novel products is significantly affected by new product trials (Sugandini et al., 2018). IoMT being a new and novel concept, this factor namely novelty-seeking behaviour was also considered important for this research as a moderator of the relationship between motivation and training on the one hand and continuous intention to use IoMT on the other. In addition, technology is changing rapidly. One such technology that is attracting the attention of researchers in recent times is Artificial Intelligence (AI) (Almansoori et al., 2021; Neubauer, 2021). IoT is not an exception and is affected by AI because it is entirely technology-based (Osifeko et al., 2020).

If one argues that technology is a phenomenon that affects any field including IoT, awareness about the impact of those technologies on the users inevitably becomes a major concern. The reason for this is that the technological innovations tend to be complex and understanding those technologies for continuous use becomes imperative (Chen, 2018). In such a situation using those technologies becomes a challenge and therefore there is a need to know how awareness or lack of it affects the users at various stages. For instance, Chen (2018) showed that the relationship between the factors concerning technological innovation and the adoption of artificial intelligence could be moderated by many factors, for instance, awareness. In another instance, Li et al. (2016) investigated the relationship between cyber security awareness and its impact on employee behaviour in the context of employees in various firms in the US and suggested that the moderating effect of cyber security policy awareness level should be investigated on employees' behaviour.

To the knowledge of the researcher and a thorough search through different electronic databases revealed that no investigation has been conducted to the date about the moderating effect of artificial intelligence or its awareness of the relationship between any two factors in the conceptual model that concerns diffusing IoMT. Therefore, there is a lack of knowledge on how AI embedded in IoMT acts as a moderator in an investigation related to continuous intention to use IoMT. These examples show the existence of a gap in the literature and the confusion related to how awareness about new technology, in particular AI, moderates the diffusion of IoMT, an area that is open for investigation. At this point it is worthwhile to understand what is intention to use, continuous intention to use and acceptance of a technology before proceeding to review the continuous intention to use IoMT.

- **Intention to use**

The intention to use is defined by (Ajzen, 1991) as how the user intends to use technology in the future. Despite the fact that (DeLone and McLean, 2003) argue that "use" is a suitable metric in the original IS Success Model, the straightforward definition of "use" is in fact unable to provide sufficient justifications in terms of the considerations of the degree, nature, quality, and suitability of the term "use." In order to illustrate further the context of the variable "use," DeLone and McLean (2003) use "intention to use" as an alternate variable in the updated IS Success Model. This is a result of the controversy around whether use can be considered a successful indicator of IS (Seddon, 1997).

The association between perceived usefulness and perceived ease of use is used to indicate the extent to which an individual has intentionally decided to engage in or refrain from engaging in any certain future behaviour. Both elements have an impact on the intention to use technology (Brezavšček et al., 2016). According to DeLone and McLean (2003) the 'Intention to use' is an attitude, whereas 'use' is a behaviour. Also, Teo & Zhou (2014) explain that intention to use is a measure of a user's future intention to utilise technology.

- **Continuous intention to use**

Continuance intention is defined as the user's choice to keep using a particular item or service they have already been using, it differs from first-time usage (Kuo & Hsu, 2022; Lee & Kwon, 2011; Wu & Wang, 2006). Similarly, Bhattacherjee (2001) explains that continuous intention is the continual usage or re-use of a specific system by an individual. According to (Islam, 2011) that the success of any technology relies on the willingness of the users to continue using it. Previous research has suggested that continuous intention has a direct and important influence on actual usage (Cheng and Yuen 2018; Joo et al. 2016).

- **Technology acceptance**

Technology acceptance is a mindset toward technology that comes before technology adoption and is impacted by a variety of circumstances (Granić, 2022). According to Teo

(2011), acceptance refers to a user's readiness and willingness to use technology for the purposes for which it is intended.

From the above, it is possible to summarise that intention to use a technology or new technology is preceded by the acceptance of the technology by the person. Onceaccepted, it leads the person to intend to use the technology. However continuous intention to use is a stage where the person has intended to use, actually started using, and continued to use without break or reuse as a matter of choice even when the person comes across a new technology or an innovation.

2.7. Continuous Intention to use IoMT

New technology usage should be widespread and must provide better support to the patients. Here it must be understood that usage of IoMT is meant to be continuous usage of IoMT and not one-time usage. Therefore, in this chapter, the term usage refers to continuous usage and not one-time usage. This argument is consistent with the opinion of other researchers who have interchangeably used usage and continuous intention to use (e.g., Tam et al., 2018; Li et al. 2018; Abdullateef et al. 2015; Hong et al., 2015). Bhattacherjee (2001a) explains that prior post-adoption research in the field of IS researchers has focused essentially on one single post-adoption behaviour usage namely continuance usage. It is argued in the literature that retaining users as part of the continuance usage has become important for many industries including the field of healthcare (Tam et al., 2020). Further Venkatesh et al., (2011) point out that the long-term viability of innovation depends more on users' continuance behaviour than their initial decision to adopt innovations. This argument implies that there is a need to understand how users develop the idea of continuance intention to use an innovation which is an important knowledge that needs to be gained for the benefit of manufacturers, suppliers and healthcare professionals.

2.7.1. Theoretical aspects concerning Conceptualising IoMT and Continuous Intention to use IoMT

Some of the theories that have addressed various usage and user intention of technology include the Theory of Reasoned Action (TRA), Technology Acceptance Model (TAM), the

Theory of Planned Behaviour (TPB), theory of Diffusion of Innovation (DoI), Task Technology Fit (TTF) and Unified Theory of Acceptance and Use of Technology (UTAUT). While usage of technology has been a widely researched factor in the literature at the same time more and more models are still being developed based on the abovementioned theories to explain the usage of technology by consumers and others as well as determine the behavioural intention to use or adapt technology indicating the depth of knowledge that still needs to be unearthed about the concept of usage of technology (Lee & Lee, 2020; Park et al., 2020; Ahmad et al., 2020; Kang, 2019; Prayoga & Abraham, 2016; Jin et al., 2013). It also indicates the limitations that exist in the current literature concerning the conceptualisation of usage of technology or the behavioural intention of people to use technology (Kim et al., 2019; jin et al., 2013).

To understand the concept of usage of IoMT a review of the literature was undertaken. Several factors are influencing the usage of IoT and IoMT. For instance, Ahmed et al. (2020) investigated the IoT service behavioural intention to use IoMT of smart mobility in Malaysia using the factors such as attitude, behavioural intention, digital dexterity, efficiency, functionality, intrusiveness concerns, IoT-service quality, perceived ease of use, perceived usefulness, privacy, social electronic word of mouth, subjective norm and tangibility. In another instance, Baudier et al. (2019) investigated the employees' behavioural intention to use the healthcare internet of things related to wearable devices as a source of innovation in corporate HR policies and used the factors self-healing, self-association, self-design, self-discipline, self-entertainment, motivations, integrity, benevolence, perceived ease of use, perceived usefulness and attitude as determinants. Furthermore, Salleha and Daud (2019) investigated the impact of diffusion of innovation factors namely relative advantage, compatibility, complexity, observability and trialability on the internet usage of things in the context of Malaysia. Similarly, Ahmad et al. (2020) investigated the impact of perceived usefulness, perceived ease of use, perceived credibility, perceived irreplaceability, compatibility and social influence on continuous intention to use digital health wearables in the context of elderly, diabetic patients in Bangladesh. More examples can be found in the literature that have investigated the determinants of the behavioural intention to adopt IoT and IoMT and continuous intention to use IoMT (e.g., Padyab et al., 2019; Jiang et al., 2019; Jalali et al., 2017).

2.7.2. Operationalising the concept of Continuous Intention to use IoMT

An important aspect of the research conducted so far in the literature relevant to intention to use behaviour is that the various factors that have been used to determine use of IoMT or continuous intention to use IoMT as a variable, have been conceptualised in more than one way in different models. For instance, in the model tested by Ahmed et al. (2020), the independent variables were digital dexterity, IoT service quality and intrusiveness concerns while perceived ease of use, perceived usefulness and attitude were used as mediating variables. Similarly, in the model developed by Baudier et al. (2019) factors namely self-healing, self-association, self-design, self-discipline, self-entertainment were used as independent variables, while motivation, perceived usefulness, perceived ease of use and attitude were used as mediating variables to explain the behavioural intention to use internet of health things. This indicates that there can be a number of factors related to behavioural attributes that could be used to determine the continuous intention to use IoMT as part of a larger concept of behavioural science. Deeper knowledge about how to manipulate usage of IoMT a derivative of IoT, as a construct, using determinants could help in determining potential behaviour of healthcare professional to their intention to continuously use IoMT. These discussions point out to the fact the current literature is incomplete in regard to understanding various factors not investigated so far in determination of behavioural aspects of healthcare professionals using IoMT. For instance, Ahmad et al. (2020) suggested constructs like health literacy and health believe could be used to understand their impact on the continuous intention to use digital health wearables in context of elderly, diabetic patients. Similarly, Kim et al. (2019) suggested that further investigation needs to be conducted to understand the influence of behavioural attributes like motivation and usage behaviour on the continuance intention to use online and offline accommodation application services in the context of the hospitality industry in Korea.

Finally, one of the latest publications found in the literature published by Lin (2021) indicates that more research needs to be conducted about understanding the adoption behaviour of users of recurrent innovation and the features that have an impact on the process of adoption. This implies that there is a need to conduct further indication on the continuous intention to use innovations (recurrent innovation) and the factors that impact continuous intention to use (motivation to use innovation). As an extension to the above arguments, it can be inferred that IoMT as an innovation, continuous intention to use IoMT as innovation and the extent of diffusion of IoMT into the market are areas that need further study in the context of the healthcare sector (Hartono et al., 2021; Saarikko et al., 2020). Further, it is necessary to investigate those factors that could determine IoMT usage behaviour of healthcare professionals that have not been researched yet that includes behavioural attributes and diffusion factors. These factors are discussed next.

2.7.3. Measurement of Continuous Intention to use IoMT

Literature shows that measurement of usage has been carried out by different authors under different contexts and using different theories. For instance, Gao and Bai (2014) used the scale developed by Venkatesh (2000) to measure the behavioural intention to use IoT. Similarly, Al-Gahtani (2016) used the scale developed by Venkatesh and Bala (2008) to measure the behavioural intention of e-learning acceptance and assimilation of students. Lee et al. (2011) used the scale developed by Davis et al. (1989) to measure the behavioural intention of employees to use e-learning systems. Niknejad et al. (2018) used a scale developed by Venkatesh (2012) to measure the behavioural intention to use wellness wearables which included items concerning the continuous intention to use wellness wearables. These measuring scales are based on multipoint Likert type scales. The information is given above clearly articulates that behavioural or continuous intention to use IoMT as a variable could be measured by a variety of instruments available in the literature that have been already validated through prior measurement in empirical studies. It is possible to adapt the most suitable measurement instrument to this research.

2.8. Usage Behaviour Theories

Some of the widely used theories related to usage behaviour include the Theory of Reasoned Action (TRA), Technology Acceptance Model (TAM), the Theory of Planned Behaviour (TPB), the theory of Diffusion of Innovation (DoI), Task Technology Fit (TTF), Expectation Confirmation Theory (ECT) and the Unified Theory of Acceptance and Use of Technology (UTAUT, UTAUT-2). Some of these are discussed next to find their suitability for application in this research concerning the core issue of determining the continuous intention of healthcare professionals to use IoMT.

2.8.1. Theory of Planned Behaviour

Figure 2.1 provides the diagrammatic representation of the theory of planned behaviour (TPB). Theory of Planned Behaviour (TPB) is a psychosocial theory (Taherdoost, 2018; Gagnon et al., 2006; Pierro et al., 2003) developed by (Ajzen (1991) which is an extension of TRA (Fishbein & Ajzen, 1975), that has dominated health-related behaviour research for the last three decades (Sniehotta et al., 2014).

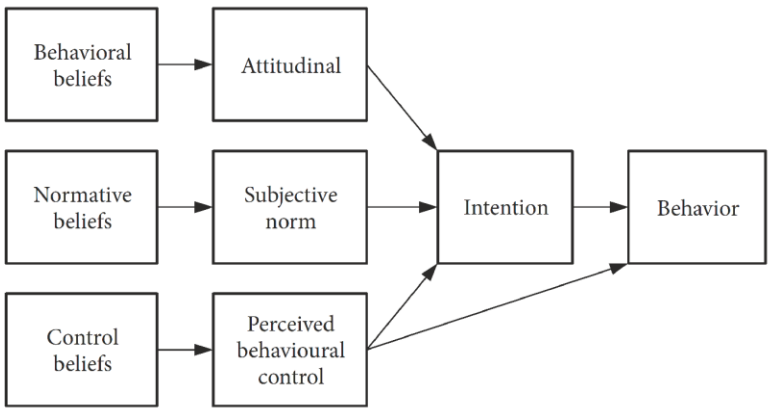


Figure 2.1: Theory of planned behaviour (Ajzen, 1991)

TPB investigates the effects of users' views on technology adoption (Shang et al., 2021) and earned strong empirical evidence for behavioural determination of IS and other areas (Olushola and Abiola, 2017). Additionally, it is used primarily to study human intentions and attitudes (Ajzen, 1985; 1991). According to TPB user's behaviour is influenced by their intention to behave whereas the intention is influenced by attitude, subjective norms, and perceptions of behavioural control (Septiani & Ridlwan, 2020). It is commonly utilised to anticipate intention and behaviour in the context of technology adoption in the medical field (Bronfman et al., 2021; Hennings & Herstatt, 2019; Ifinedo, 2018). The study by Koul and Eydgahi (2017) indicated that when a study focuses on the potential adoption of emerging technology, TPB is considered applicable and helpful. One of the latest research papers investigating medical tourism indicates that potential human action can be anticipated, and intention clarified by applying TPB (Boguszewicz-Kreft et al., 2020).

Macovei (2015) pointed out that the theory creates power determinaions through reasoning actions based on how a person perceives events. From the technology perspective, Herrmann and Kim (2017) argue that TPB is a suitable theory to use to comprehend technology and health behaviours. The researchers indicate further that TBP applies to health and fitness research and through their study showed that concerns of both the users and developers should have interaction concerning the long-term health behaviour change of users. Martin et al. (2007) investigated the ability of the theory of planned behaviour (TPB) to determine Mexican American children's self-reported, moderate-to-vigorous physical activity. Through this study, it was possible to understand the behavioural traits of children for instance attitudinal, intention to adopt, perceived behavioural control and perception of support of those children indicating that TPB can be applied to the study of behavioural traits in the field of physical education but not related to technology. This example shows that TPB is more oriented towards determining the psychological factors concerning behaviour but not adoption behaviour concerning technology. Examples of the application of TPB in research are provided below.

The theory's determinaion aspect has enabled healthcare personnel to find out means of providing proper healing for environmental and psychological-related ailments as discussed by Millstein (1996). For example, the use of condoms was linked by this theory to control the behaviour and attitudes of people towards sex urges, according to the suggestion by Hafetz (2010). Jokonya (2017) stated that TPB has gained remarkable momentum in IS and IT research areas for instance internet banking and e-commerce etc. Since Mobile learning is increasingly becoming more important and plays a critical role in a fast-growing technology (Han & Shin., 2016). The study (Azizi and Khatony, 2019) used TPB theory to examine the factors affecting the intention of medical science students to adopt mobile learning that shows the TPB-based model was an effective model to recognise psychological factors that influence the medical science students' intention to use m-leaning.

Despite the theory's extensive use, the TPB has been criticised for ignoring moral considerations (Karimi & Saghaleini, 2021; Si et al., 2020). Furthermore, Jokonya (2015) argued that TPB is not a suitable theory since it has flaws including the exclusion of habits and lacking explanatory power when testing multiple IS contexts because its basic constructs do not accurately describe every situation. A detailed description of the strengths and weaknesses of TPB is provided next.

2.8.2. Strengths and Weaknesses of the Theory of Planned Behaviour

Despite its strengths, the theory of planned behaviour has been criticized because it focuses on cognitive factors and for the lack of impact on adoption behaviour and its identity as a model that can determine adoption behaviour beyond the field of psychology (Maio et al., 2018) (Appendix 3).

2.9. The Theory of Diffusion of Innovation (DoI)

Figure 2.2. Provides a holistic representation of the various aspects concerning the diffusion of innovation and the rate of its adoption. This theory was developed by Rogers (1983) who analysed thousands of innovation studies and elucidated five characteristics that were part of the stage of innovation namely relative advantage, compatibility, complexity, observability and trialability (Moore & Benbasat, 1991).

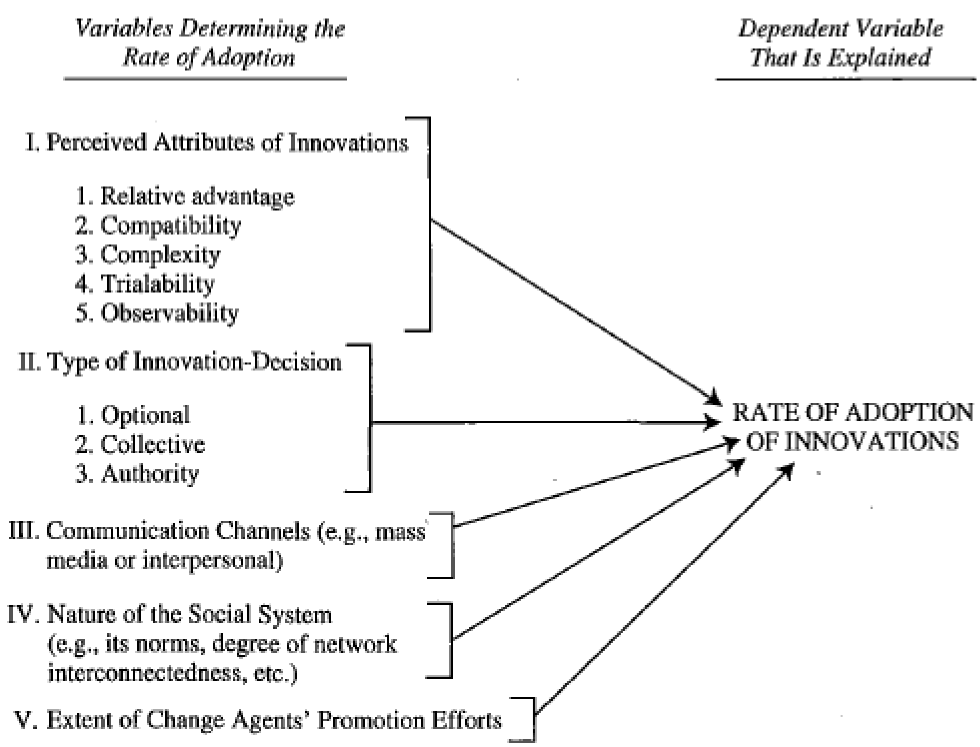


Figure 2.2: Determinants of the rate of adoption of innovations (Rogers, 1983).

This theory has been widely used in research concerning many disciplines including education, sociology, healthcare, communication, agriculture, marketing, and information technology (Emani et al. 2018; Lee et al. 2011). In studies concerning health informatics the diffusion of innovation (DoI) theory is highly recommended. Ward (2013) and Zhang et al. (2015) concurred that DoI theory is a useful theory in conceptualising technology adoption in the eHealth context.

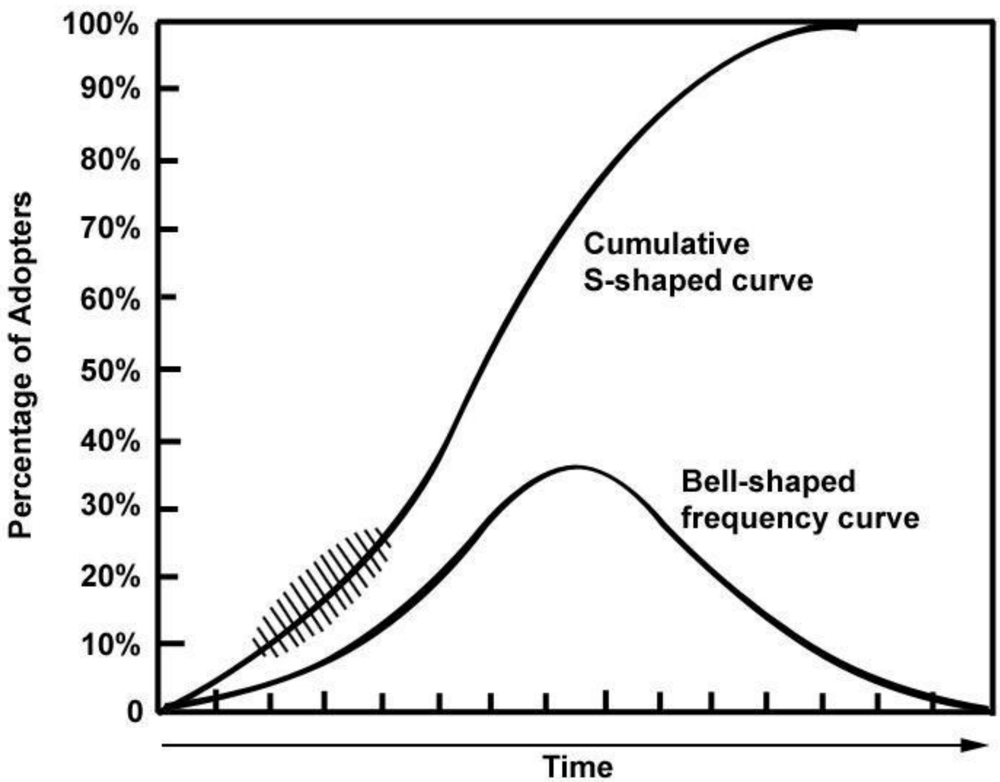


Figure 2.3: Cumulative S-shaped' curve

In addition to the above Rogers (2003) argues that the beginning and end of the diffusion of innovation can be plotted through an 's-shaped' curve. This is depicted in figure 2.3. Figure 2.3 shows the time variable as a function of the percentage of adopters. This allows the classification of adopters into categories as well as plot diffusion curves. According to Rogers (1983; p.243) adoption of innovation amongst users follows a normal, bell-shaped curve when plotted overtime on a frequency basis and the adoption data could be depicted by either a bell-shaped curve or an s-shaped curve when the cumulative number of adopters are taken into account. In figure 2.3 the two curves have been drawn for the same data concerning the adoption of innovation over time by the members of a social system. While the bell-shaped graph shows the plotting of the data in terms of the number of members of the social system adopted each year, the s-shaped curve indicates the graph for the data related to the cumulative number of individuals in the social system. The shaded area on the graph indicates the time during which the s-curve of diffusion “takes-off”. The initial section of the s-curve indicates the slow pace at which the adopter distribution rises when the number of adopters is only a few in each time period but accelerates thereafter to a maximum till about half of the members of the social system have adopted the innovation. Beyond this point the adoption rate increases gradually at a slower rate when the remaining few individuals finally adopt the innovation. It must be noted here that the s-shaped curve is normally distributed (Rogers, 1983). Although the s-curve provides information about the cumulative distribution of adoption of the innovation, researchers argue that the s-shape is not always symmetrical and it may depend on specific social systems and type of innovation (Rogers, 2003; Geroski, 2000; Fichman, 1992). In addition, Mohr (1987) points out that it is not fully known when or why the curve applies. These criticisms need to be taken into account while explaining the beginning and completion of the diffusion of an innovation.

2.9.1. Stages of DoI

Diffusion of innovations is a study and practice paradigm that can be applied to the complex setting of health care for both explanatory and interventional reasons (Dearing and Cox, 2018). It is considered a major advantage for organisations since it causes social change and changes the structure and operation of a system (Barrane et al., 2018). According to Dearing and Cox (2018) diffusion can be defined as a social process or phenomenon in which people spread information about an invention, such as a new evidence-based technique for expanding or enhancing health care. The process of adopting new inventions has been investigated and studied for more than forty years. Diffusion of innovation theory is a theory that describes how new ideas spread from one place to another. Researchers have extensively employed Rogers' DoI theory, which was developed in 1962 to analyse IT innovations concerning both individuals and organisations (Tu, 2018). The four major parts of DoI theory, according to Rogers (2003) are innovation, communications channels, time, and social systems.

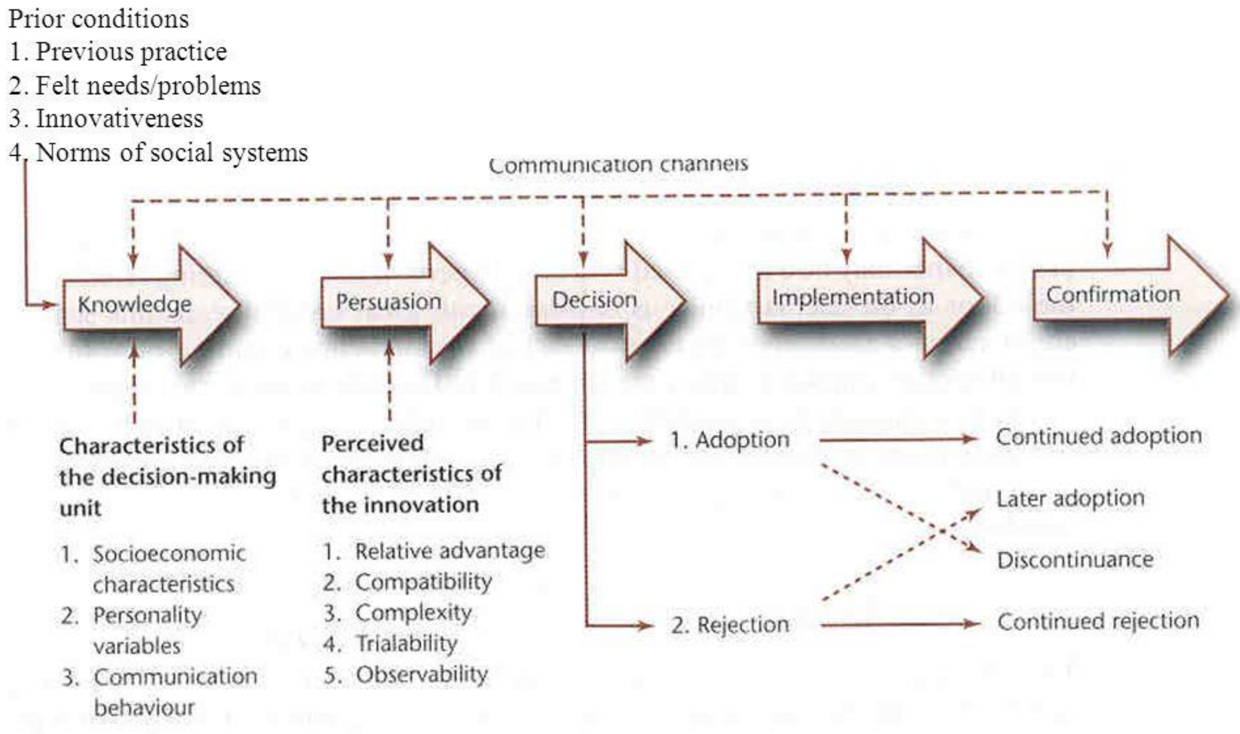


Figure 2.4: Five steps in innovation decision process (Rogers, 1983).

Rogers (2003) focused on the elements that drove innovation adoption and developed the five stages of the innovation decision-making process (Figure 2.4). These five steps outline the decision-making process that an individual or organisation goes through when determining whether or not to embrace, accept or reject an invention (Rogers, 2003, p. 168-169).

Based on the above description of DoI, the review focused on the utility of this theory for this research.

2.9.2. Rogers' four main elements involved in the Diffusion process of an Innovation

Diffusion, as defined by Rogers (1983; p.5), is the process by which an innovation is communicated through some channels amongst members of a social group over time. According to Gabriel and Da Silva (2017) communication channels are required to communicate developments taking place about an individual or an organisation. Communication is defined as the way by which messages (information) are transmitted from one individual to another. The diffusion process relies heavily on communication (Gabriel & Da Silva, 2017). As mentioned in the previous section there are four elements of diffusion as defined by Rogers (1983) namely innovation, communication channels, time, and social systems. Each one of the four main elements are described next to know their importance or otherwise for this research.

- **Innovation**

Rogers described diffusion as “the process by which an innovation is communicated through certain channels over time among the members of a social system” (Rogers, 2003, p. 5) and defined innovation as “an idea, practice, or object perceived as new by an individual or other unit of adoption” (Rogers, 2003, p. 12), given the prevalence of technological advancements in diffusion research, Rogers (2003) frequently used the terms "technology" and "innovation" interchangeably. The above definition can also be applied to IoMT as an innovation. It is an idea and practice that is diffusing into the healthcare market and many healthcare organisations including hospitals have adopted IoMT (Harst et al., 2019). Furthermore, the concept of IoMT is supported by another important technological advancement namely AI which indicates that not only IoMT is diffusing but also AI is diffusing alongside IoMT and is contributing to the diffusion (Almansoori et al., 2021; Vemuri et al. 2020). Here it can be seen that AI plays a role in enabling the diffusion of IoMT.

Furthermore, even if an innovation has been around for a long time, it may still be considered novel by some people. The three steps (knowledge, persuasion, and decision) of the innovation-choice process, which will be discussed later, are more closely tied to the newness feature of an adoption. Rogers suggested that there is a scarcity of diffusion studies on technological clusters. “A technology cluster,” according to Rogers (2003), “consists of one or more distinguishable elements of technology that are perceived to be closely interrelated” (p. 14). This points toward the novelty-seeking behaviour of users of IoMT. Based on the discussions above it is possible to interpret that IoMT as innovation can diffuse and has the potential to be accepted by healthcare professionals because it is an innovation; it is possible that diffusion could be assisted by AI and novelty-seeking behaviour of healthcare professionals’ knowledge about which is not found in the extant literature. Furthermore, literature shows that innovation attributes that need to be considered when the innovation is diffusing have been identified as relative advantage, compatibility, complexity, trialability and observability.

- **Communication channels**

Communication channels are defined as how people get knowledge about the innovation and assess its use which entails both mass media and interpersonal communication (Zhang et al., 2015). According to Rogers 2003, p. 18) the second component of diffusion is communication channels, which are defined as "how messages are transmitted from one individual to another". The conditions under which a source will or will not transmit the innovation to the receiver, as well as the consequences of the transfer, are determined by the nature of the information-exchange connection between a pair of persons (Rogers, 2003, p. 18). Both mass media and social media are used as communication channels, for instance, the radio and television, and interpersonal communication (face-to-face interactions), where the early inventors or adopters are influenced by external communications. However, the speed and nature of the diffusion process are influenced by interpersonal communications over time. Rogers (2003; p. 18) defines communication as "a process in which participants create and share information to reach a mutual understanding". Communication, according to Rogers and Kincaid (1981), is a two-way process of convergence rather than a one-way, linear act in which one person seeks to send a message to another to achieve specific outcomes. If one applies the above arguments to the process of diffusion of IoMT supported by AI, it can be inferred that communication channels will play a leading role in motivating or training the healthcare professionals leading to their continuous intention behaviour to use IoMT. It can also be inferred that such a behaviour can be subjected to both positive and negative transmission of information about IoMT which in turn can affect the final adoption by the healthcare professionals. Whether this indeed is the situation needs to be investigated.

- **Time**

According to Rogers (2003), most behavioural-based research efforts ignore the time factor and claim that one of diffusion research's benefits is that it incorporates the time dimension. Time is factored into the invention dissemination process, adopter categorisation, and adoption rate. Time has three effects on the diffusion process (Rogers, 2003, p. 20). First, there is the innovation-decision process, which is the mental process through which an individual progresses from personal knowledge of an innovation to establish an attitude toward it either adopting or rejecting it. Second, when it comes to the inventive ability of an individual or unit of adoption, innovativeness is defined by Rogers as “the degree to which an individual or unit of adoption is relatively earlier in adopting new ideas than other members of a social system” (Rogers, 2003, p23). Third, the rate of adoption of an invention in a system is usually determined by the number of people who use the system and tend to accept the innovation in a specific time (Rogers, 2003, p. 23). Applying these concepts to the diffusion of IoMT, it is seen that IoMT can be accepted and used continuously at different periods by different users, determining adoption difficult as most of the theories talk of adoption at one point of time only as time is not a consideration in many adoption theories including TRA, TPB, TAM and UTAUT (Heinsch et al., 2021). Since continuous intention to use a technology which is the core issue of this research is related to repeated use of technology, DoI explains how this repeated use of technology could take place, a concept that is not used in the investigations concerning the diffusion of IoMT. Studies addressing the pre- and post-acceptance of IoMT are hard to find in the contemporary literature.

- **Social system**

In the diffusion process, the social system is the last component, according to Rogers (2003), " a set of interrelated units engaged in joint problem solving to accomplish a common goal" (p. 23). Because innovation spread occurs inside a social system, it is influenced by the social structure of that system. Rogers (2003) explained the structure of a social system influences people's attitudes toward innovation and, as a result, the rate at which ideas are adopted. He also continued by asserting that the essence of the social system has an impact on people's innovativeness, which is the primary criterion for classifying adopters.

2.9.3. Current knowledge about DoI concerning Continuous Intention to use IoMT

According to Karahanna et al. (1999) different behavioural intentions are reflected by the adoption and continued use of an information technology innovation and pointed out that information technology adoption is the initial use (new behaviour) of information technology innovation at the individual level. Continuing to explain the concept of adoption of information technology Karahanna et al. (1999) say that using information technology innovation is the subsequent actions at the individual level after its adoption.

Consequently, factors that assess user acceptance of an information technology innovation vary from those that influence the attitudes of users towards the continued usage of the IT innovation. DoI theory has been previously used to study the adoption and individual use of new information technology in the healthcare sector such as Telehealth and shared electronic records (Helitzer, et al., 2003; Greenhalgh et al., 2008). Additionally, diffusion of innovation theory has been used to measure the understanding of certain technologies to understand the internet use of family physicians (Chew et al., 2004). Furthermore, the DoI theory has been applied in qualitative analysis to investigate the adoption and usage by Taiwanese nurses of a computerised nursing care program (Lee, 2004). Another researcher analysed the factors influencing patient acceptance and use of consumer e-health innovations in primary care clinics (Zhang et al., 2015). Also, it was used to identify the factors that advance evidence-based practice (EBP) adoption (Mohammadi et al., 2018) and influence the adoption and usage of eHealth technologies in Ghana (Kesse-Tachi et al., 2019). Some of the recent implementations of DoI theory in research include the research conducted by Talebian and Mishra (2018) who predicted the adoption of autonomous connected vehicles using DoI as well as the one conducted by Wong (2018) concerning autonomous rail and passenger-vehicle technology for the public.

Furthermore, meta-studies on Roger's theory of innovation show that in the process of diffusion of innovation five classifications could be made on the statistical distribution of adopter innovativeness based on time of behavioural intention to use IoMT. These are called innovators (2.5%), early adopters (13.5%), early majority (34%), late majority (34%) and laggards (16%) (Rogers, 2003). Amongst these adopters, it is seen that the early majority and late majority comprise 34% each accounting for most (68%) of the adopters. This knowledge can help in investigations that require the determination of the behavioural intention of users of innovation although it may not be entirely possible to group users within the statistical limits of distribution of users concerned with innovations provided by Rogers. While the above discussions provide an idea about the theory of DoI, it is important to understand its strengths and weaknesses to know how to tackle the weaknesses while applying the theory to multiple disciplines.

2.9.4. Strengths and Weaknesses of DoI

There is several strengths and weaknesses of applying DoI to innovations including IoMT. These are tabulated in Appendix 4. The strengths of DoI provide the basis to apply the theory in areas where perceiving the use of innovations is considered more important than the innovation itself. Primary characteristics of innovations could vary widely and the result of the understanding of such a variation could mean different things to different people. For instance, the internet as an invention was perceived to be harmful initially because it provided access to various types of information (e.g., information related to certain material usually restricted to adults could be harmful if accessed by children and adolescents) that can be considered potentially unacceptable to specific culture and segment of the population. However, the perception of the use of the internet as an invention provides a different view. For example, the internet is widely used to transmit and receive messages at speeds never seen before, which makes people perceive it as a great advantage to overcome distance and time, which are relatively advantageous and compatible with users. Thus, unlike any other theory, the strength of DoI provides an opportunity to understand how people perceive the use of the innovation rather than the features of the innovation itself.

According to Rogers (1995) apart from innovation, it is the diffusion of innovation that also needs to be considered while understanding the actual use of the innovation. Rogers argued that innovation is “an idea, practice, or object that is perceived as new by an individual or another unit of behavioural intention to use IoMT” (Rogers, 1995, p. 11) whereas diffusion is “the process by which an innovation is communicated through certain channels over time among the members of a social system” (Rogers, 1995, p. 5). It can be argued that innovation and its diffusion create perceptions in the minds of users about the innovation as well as its use which eventually lead to decision making by the users to either use or reject the innovation. Thus, both the innovation and its diffusion are necessary if one has to understand the potential use of an innovation. In this situation, researchers argue the understanding of the five characteristics of the use of innovation namely relative advantage, compatibility, complexity, observability and trialability described by Rogers will become important elements to predict the diffusion and usage of an innovation or behavioural intention to use innovation (Ahmad et al., 2018; Emani et al., 2018; Lee et al., 2011). When the innovation is communicated to users through appropriate channels then the users perceive the use of the innovation through either all the five characteristics of the innovation or some of them. It is useful to note here that there are research outcomes that have pointed out that only some of the five characteristics and not all the five, could be enough to determine the usage of innovation. For instance, Prause (2019) used only three characteristics of innovation namely relative advantage, complexity and compatibility in a study concerning the behavioural intention to use IoMT of Industry 4.0 standards in SMEs in Japan whereas Al-Rahmi et al. (2019) used all the five characteristics in their study of students' intention to use e-learning systems and Emani et al. (2018) found only relative advantage and trialability as useful in their investigation of perceptions of adopters versus non-adopters of a patient portal. These variations in the use of the concept of innovation and its diffusion provide reasonable flexibility in understanding the users' perception and intention to use an innovation. However, there is no consensus amongst the researchers about why all the five factors identified by Rogers still need to be used in every research concerning DoI if some of the factors are not found to predict the adoption of technology. In addition, the literature is silent on which of the five factors need to be used always and which need not be used. These aspects make it difficult for the researchers to ignore any particular set of DoI factors as not useful or include any other particular set of factors as always useful. In this situation, there is a need to investigate the influence of all the five factors in any research that concerns the diffusion of innovation and its subsequent adoption. IoMT is one such field where its diffusion needs to be studied using the five factors of DoI as current research outcomes have not provided any comprehensive indication of the need to exclude any of the five DoI factors regarding IoMT research. This is a gap in the literature.

2.10. Unified Theory of Acceptance and Use of Technology (UTAUT)

The Unified theory of acceptance and use of technology (UTAUT) model is provided in figure 2.5. This model was developed by Venkatesh and other scholars (Venkatesh et al. 2012) to determine technology acceptance in society.

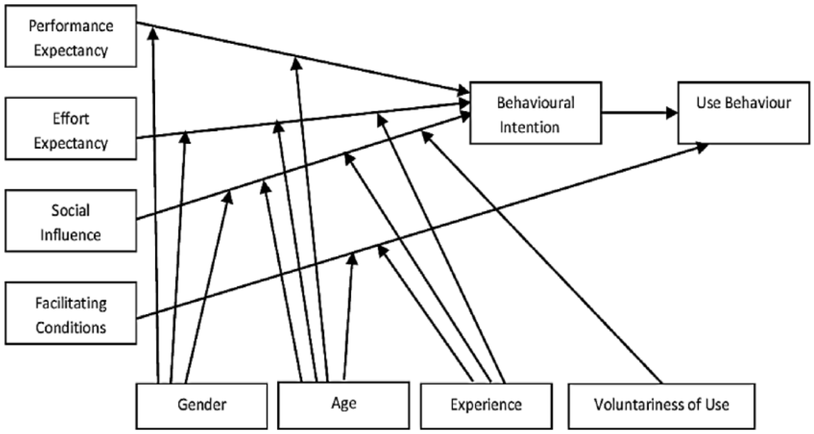


Figure 2.5: Unified Theory of Acceptance and Use of Technology (UTAUT) (Venkatesh et al. 2003).

This model seeks to explain the intentions of users in the use of information systems and their resulting behaviours. UTAUT model states that four parameters are vital in the acceptance of new technology. These parameters include performance expectancy, effort expectancy, social influence, and other facilitating conditions. Other moderators influence the model, which include age, gender, experience, and willingness to volunteer during the behavioural intention to use the IoMT process (Venkatesh et al., 2012). This theory came into existence after a thorough review of other models that were previously used by early researchers to explain the behaviours of information system users. The various theories that makeup UTAUT are provided in figure 2.6.

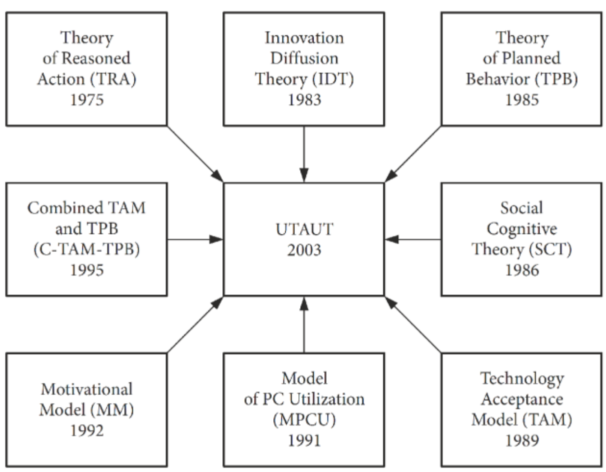


Figure 2.6: Theories that are used to construct UTAUT (Venkatesh et al. 2003).

The development of this model aimed at presenting a complete view of acceptance and the willingness of people to utilise the new technology (Zuiderwijk et al., 2015). UTAUT brought together eight adoption theories namely TRA, TAM/TAM2, motivation model

(MM), TPB, combined TAM and TPB (C-TAM-TPB), a model of PC utilization (MPCU), DoI, and social cognitive theory (SCT) (Haron et al., 2021; Kim et al., 2015). It has been used in many studies in the healthcare field. For instance, Kim et al. (2015) applied the UTAUT model to determine the intention to use technology in the context of healthcare service providers. After the invention of electronic medical records technology (EHR), in Bangladesh, the UTAUT model was used to analyse what physicians intended when using EHR technology to figure out the factors influencing the medics' adoption of the EHR system (Hossain et al., 2019). The model gave vital practical guidelines to healthcare providers explaining the importance of using EHR technology and the usefulness of such a system. This theory also analysed the factors that impacted the acceptance of Telemedicine Equipment by clinicians (Berler & Apostolakis, 2017). Also, this model was used by Laius et al. (2018) to understand home care patients and their attitudes toward Telemedicine and E-prescription. A similar study by Solangi et al. (2017) used the theory to evaluate the acceptance and use of the internet of medical things by physicians, specialists, and patients in underserved areas of the Islamic Republic of Pakistan. Although widely used, UTAUT needs to be analysed concerning its strength and weaknesses to know its utility for the current research. This is provided next.

2.10.1. Strengths and weaknesses of UTAUT

There are several strengths and weaknesses of UTAUT that need to be considered in investigations concerning innovations including IoMT. These are tabulated in Appendix 5. it can be seen that UTAUT suffers from weaknesses which are somewhat stronger than its strengths. And due to the combination of eight adoption theories, UTAUT has become complex and is not easy to apply (Bagozzi, 2007). For instance, UTAUT is criticised to be not generalisable which makes its application to all contexts difficult. Similarly, it is pointed out by researchers (e.g., Al-Tarawneh, 2019); Venkatesh et al. 2012) that this theory is more oriented toward employees as far as technology behavioural intention to use is concerned, which restricts its use in understanding the continuous intention to use IoMT.

2.11. Unified Theory of Acceptance and Use of Technology (UTAUT-2)

UTAUT-2 is an expansion on the original UTAUT explained in the previous section. UTAUT-2 is depicted in figure 2.7.

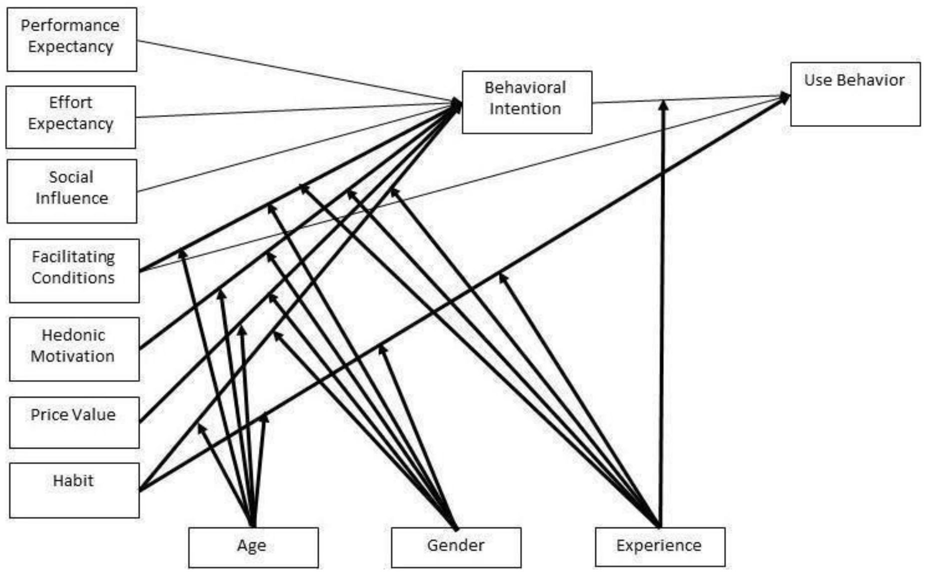


Figure 2.7: UTAUT2 Model (Venkatesh et al., 2012)

The unified theory of acceptance and use of technology (UTAUT2) is expanded by (Venkatesh, 2012) to examine acceptance and usage of technology in a consumer context. (Venkatesh et al., 2012). Hedonic motivation, price value, and habit are three constructs that UTAUT2 includes in the original UTAUT. Venkatesh et al. (2012) defined hedonic motivation as (the degree to which new technology is regarded as joyful), price value (the economic costs of new technology usage in relation to perceived advantages), and habit (the routines and time made aside to utilize new technology).

The impacts of these factors on behavioural intention and technology use are thought to be moderated by individual differences such as name, age, gender, and experience. Literature results demonstrated that as compared to UTAUT, the extensions suggested in UTAUT2 significantly improved the variation explained in behavioural intention (from 56% to 74%) and technology use (40% to 52%) (Chang, 2012). Venkatesh et al (2012)'s data also showed that age, gender, and experience all moderate the impact of hedonic motivation on behavioural intention as well as the impact of price value on behavioural intention. Habit also has both direct and mediated effects on technology use, and these effects are also moderated by individual differences (Chang, 2012).

There has been a significant improvement in the explained variance of both behavioural intention and technology use as a result of UTAUT2 (Jang et al., 2016). UTAUT2, which is a more contemporary model than the original UTAUT, has also been modified to fit various scenarios (Herrero et al., 2017). However, (Schmitz et al., 2022) indicated that UTAUT2 hasn't been applied in the context of end-user acceptance of telemedicine. Considering the fact that UIAUT provided a sufficient basis for discussing the importance of the moderators investigated under this research UTAUT-2 was not reviewed in detail.

2.12. Expectation Confirmation Theory (ECT)

The marketing industry commonly uses Oliver's (1980) expectation confirmation theory. The expectation confirmation theory (ECT) is a typical feature for predicting and explaining satisfaction and continuing behaviour (Bhattacherjee, 2001; Wang et al., 2021; Lin et al., 2009). The main limitation of ECT was that it focuses on consumer repurchase intentions which cannot capture the quality parameters of certain products in services, for instance, information system services and products. The expectation confirmation model (ECM) was developed to investigate the elements impacting information technology users' continuance intention (continuous use). Bhattacherjee first proposed a post-acceptance model of information technology users' continuance intention (continuous use) (Bhattacherjee, 2001). ECM is theoretically dependent on how beneficial they believe it to be, how confident they are in it, and how satisfied they are with its use (Bhattacherjee, 2001). Literature shows (Rajeh et al., 2021; Bhattacherjee, 2001) that while the expectation confirmation model (ECM) is often employed in the marketing industry, it is rarely used in the analysis of consumer satisfaction and post-purchase behaviour in the healthcare industry. However, this theory was not considered fit for this research and hence is not reviewed in detail. Some of the examples of the application of the technology adoption theories are compiled (Table 2-3, 2-4 & 2-5).

Table 2-3: Examples of application of DOI theory

	Author/s	Theory	Field of study	Actual technology	Users	Important constructs
DOI	Talukder et al. (2019)	DOI and UTAUT2	Fitness	Fitness wearable technology (FWT)	All types of users	Performance expectancy, effort expectancy, social influence, habit, compatibility and innovativeness, FWT adoption and the intention to recommend it.
	Putteeraj et al. (2021)	DOI	Healthcare	E-Health	Healthcare workers	Relative advantage, compatibility, complexity, trialability and observability
	Marak et al. (2019)	DOI and UTAUT	Various fields	3D Printing technology	All type of users	Relative Advantage, Ease of Use, Voluntariness, trialability compatibility and observability
	Savoury (2019)	DOI and TOE	Manufacturing Sector	IoT	IT leaders	Relative advantage, complexity, compatibility, technology readiness, top management support, firm size, competitive pressure, and regulatory support and intent to adopt IoT
	Octavius & Antonio (2021)	Extended UTAUT, DOI, and the internet customer trust model.	Healthcare	mHelath	All types of users	Effort expectancy, performance expectancy, price value, Innovativeness, facilitating condition, and intention to adopt, Compatibility

Table 2-4: Examples of application of TPB

	Author/s	Theory	Field of study	Actual technology	Users	Important constructs
TPB	Alam et al. (2018)	TPB, TAM and DOI	Banking Sector	Mobile banking	Customers	Relative Advantage, Perceived Ease of Use, Compatibility, Trialability, Attitude, Social Norms, Perceived Behavior Control and Mobile Banking Adoption Intention
	Hadadgar et al. (2016)	TPB	Healthcare	Medical + education	General practitioners	perceived behavioural control Subjective norms Attitudes towards behaviour
	Haldar & Goel (2019)	TPB and TAM	Commerce	Mobile application	All users	perceived ease of use, perceived usefulness, subjective norms (SN), perceived behavioural control, attitude, and willingness to use
	Chang et al. (2016)	TPB and TAM	Tourism/ Medical	Wearable Medical Devices and application of wearable devices i	Tourists' users	Social Influence, Effort Expectancy, Intention to Use, Performance Expectancy, Facilitating Conditions, Health Consciousness and Trust

	Alam et al. (2018)	TPB, TAM and DOI	Banking Sector	Mobile banking	customers	Relative Advantage, Perceived Ease of Use, Compatibility, Trialability, Attitude, Social Norms, Perceived Behavior Control and Mobile Banking Adoption Intention

Table 2-5: Examples of application of UTAUT model

	Author/s	Theory	Field of study	Actual technology	Users	Important constructs
UTAUT	Alam et al. (2018)	TPB, TAM and DOI	Banking Sector	Mobile banking	customers	Relative Advantage, Perceived Ease of Use, Compatibility, Trialability, Attitude, Social Norms, Perceived Behavior Control and Mobile Banking Adoption Intention
	Hadadgar et al. (2016)	TPB	Healthcare	Medical + education	General practitioners	perceived behavioral control Subjective norms Attitudes towards behavior
	Haldar & Goel (2019)	TPB and TAM	Commerce	Mobile application	All users	perceived ease of use, perceived usefulness, subjective norms (SN), perceived behavioural control, attitude, and willingness to use
	Chang et al. (2016)	TPB and TAM	Tourism/ Medical	Wearable Medical Devices and application of wearable devices i	Tourists' users	Social Influence, Effort Expectancy, Intention to Use, Performance Expectancy, Facilitating Conditions, Health Consciousness and Trust

Tables 2-3 to 2-5 show that DOI, TPB and UTAUT have all been discussed and utilised in different fields in the literature including healthcare, banking, education, farming and other fields. DOI theory is considered the second-most common model used in the information technology field, although its use in other fields is not well established (Lyytinen & Damsgaard, 2001; Prescott & Conger, 1995). During the Covid 19 pandemic, the healthcare sector has been forced to fast deploy and employ IoT, smart devices, and robotics due to the IoMT's remarkable benefits of those devices to aid clinicians and patients. As a result, the number of IoMT research studies of IoMT acceptance have been increased lately, especially in Asia and the gulf region such as (Alqahtani, 2021; Umair et al., 2021; Masmali et al., 2020).

2.13. Choice of the theory to explain continuous intention to use IoMT

From the foregoing discussion it can be seen that five theories were chosen for review. To choose the theory that is most suitable for this research, it was necessary to bring continuous intention to use IoMT into perspective. IoMT is an innovation and is an extension of IoT (Korte et al., 2021). It is still evolving. It was found in section 2.6.4 above that the use of IoMT or behavioural intention of users of IoMT or continuous intention to use IoMT is not easy to determine because of the involvement of many different factors that affect users. A critical review of the relevant literature shows that the choice of the theory that could be used for this research in determining the use of IoMT by healthcare professionals or their behavioural intention to use IoMT, DoI stands out due to its ability to explain behavioural aspects of users concerning innovations like IoMT and its diffusion and its continuous intention to use (Sayginer & Ercan, 2020). Literature shows that there is a necessity to understand when IoMT is still diffusing, how to determine the acceptance and continuous usage of IoMT at different stages of the diffusion of the IoMT or just before its use when diffusion is complete or after its usage (Hartono et al., 2020). An understanding of this at multiple stages provides an opportunity to maintain the quality of the innovation or improve the features of innovation or drop the innovation and also determines the continuous intention to use the innovation (Rogers, 2003). DoI facilitates this. Other theories do not facilitate this. For instance, TAM and UTAUT are largely used to determine the behavioural intention of people to adopt a technology (Chen et al., 2020) not its usage point of view beginning from the innovation stage. Similarly, TRA and TPB are more concerned about factors that enable the determination of behavioural traits to determine the behaviour of an individual under different contexts but do not address innovation and its diffusion (Chen et al., 2020). At this stage, it can be seen that DoI happens to be the best option that could be applied to this research to explain the usage or continuous intention of healthcare professionals to use IoMT and conceptualise usage or continuous intention to use IoMT as a variable. This inference is supported by other researchers including Salleh and Daud (2019) and Karahoca et al. (2018). Thus, the following sections discuss how DoI as a theory provides the basis to extract factors that could be used to determine the continuous intention to use IoMT.

2.14. Application of the theory of Diffusion of Innovation (DoI) to determine continuous intention to use IoMT

Although much of the discussion about DoI as a theory has been discussed already in section 2.9. It is important, however, to understand how DoI as a theory can be applied to determine and determine the continuous intention to use IoMT, the central issue of this research. For instance, Hartono et al. (2020) suggest the DoI could be applied to understand the diffusion of telemedicine by identifying the factors that explain diffusion. In this context, Hartono et al. (2020) argue that the five factors that determine the diffusion of an innovation namely relative advantage, complexity, compatibility, trialability and observability could be used to understand the diffusion as well as continuous usage of telemedicine which is a form of IoMT. Warty et al. (2021) express similar sentiments and argue that the degree to which an innovation diffuses depends on aspects including the ability to challenge the dominant design and build upon it an argument supported by Suarez et al. (2015) and Utterback et al. (1993).

In addition, the acceleration of innovation to the final usage or adoption of an innovation which is part of the life cycle of the diffusion of that innovation also finds importance in the literature (Gonera et al., 2021). It is argued that interventions related to segment characteristics, personas, and perceived attributes of innovation can be used to find targeted interventions that could accelerate the diffusion of innovation (Szejda et al., 2020). Some of the interventions that have found application in accelerating innovation in the literature include motivation (Liao et al., 2021; Heinsch et al., 2021), training (Ruivo et al., 2020); workload (Furst et al., 2013), firm size (moderator) (Salah et al., 2021), national culture (Ghaleb et al., 2021) age (moderator), Venkatesh et al., 2003); technology (e.g., AI awareness (Hwang et al., 2021); government support (Ching-Wen & Ching-Chiang, 2017) and novelty seeking (Dabholkar & Bagozzi, 2002). It can be seen that not all interventions mentioned above would be reviewed in this research as it is not possible to include all the interventions in one research due to the limited time and scope of the research. Thus, only some of the interventions that have bearing on the diffusion of IoMT have been critically reviewed which include the following interventions namely motivation, training, AI awareness, novelty-seeking behaviour and age as examples that affect the diffusion of IoMT. After explaining the role of interventions in the diffusion of innovations including IoMT, the next sections review the DoI factors namely relative advantage, compatibility, complexity, observability and trialability that are central to the determination of continuous intention to use IoMT.

2.14.1. Conceptualisation of DoI factors

The five factors of DoI namely relative advantage, compatibility, complexity, observability and trialability have been highlighted as important drivers of diffusion of IoMT and its use by healthcare professionals (see section 2.9.2). Each one of these variables has been independently defined as follows by Roger (Moore & Benbasat, 1991-p.136-137; Rogers, 1983)

- **Relative Advantage:** is the degree to which an innovation is perceived as being better than its precursor.
- **Complexity:** is the degree to which an innovation is perceived as being difficult to use.
- **Compatibility:** is the degree to which an innovation is perceived as being consistent with the existing values, needs, and past experiences of potential adopters.
- **Trialability:** is the degree to which an innovation may be experimented with before behavioural intention to use IoMT.
- **Observability:** is the degree to which the results of an innovation are observable to others.

Each one of these factors has been used as an independent variable by researchers individually (Al-Rahmi et al. 2019) and collectively, as one DoI construct (Salleh & Daud, 2019). However, there is no clarity in the literature on whether the representation of the five factors by Salleh et al. (2019) could be used to measure DoI as one variable or each one of them should be used as an exogenous variable to understand how IoMT diffuses as innovation, represented by Al-Rahmi et al. (2019). The obvious advantage of using relative advantage, compatibility, complexity, observability and trialability of IoMT as independent variables is that research outcomes can see the individual operation of the factors leading to better definition and control of behavioural intention of users of IoMT. The collective representation of the factors that helps define DoI as the main construct and determine behavioural intention to use IoMT makes the model parsimonious. Nevertheless, there is no specific recommendation from researchers who have operationalized the factors using an empirical model to follow one way or the other.

However, DoI itself as a theory has been criticised to be plagued by limitations. For instance, Lyytinen and Damsgaard (2001) and Marzouki & Belkahla (2019) claimed that innovation may not necessarily meet all the stages of behavioural intention to use IoMT if a person has to adopt the innovation as described by Roger. The reason being it is always possible that behavioural intention to use IoMT occurs in a dyadic relationship and there is the possibility that borders between stages could be merged. Next Damanpour (1996) and Marzouki & Belkahla (2019) criticized DoI as a theory that cannot explain how diffusion was perceived and quantify it due to the complexity of human and human networks. Again, Lyytinen and Damsgaard (2001) and Marzouki & Belkahla (2019) highlight that not all laggards defined in the theory were lagging in reality as some of them turned out to be visionaries than the innovators. Despite such criticisms yet DoI has become a very popular model to work within research that concerns the diffusion of innovation. The following sections thus critically review the five DoI factors.

- **Relative advantage**

Literature shows that relative advantage is a construct identified by the theory of DoI and that it influences the adoption of the internet of things positively (Tu, 2018; Ma et al., 2017; Shin & Jin Park, 2017; Balaji & Roy, 2016). Examples of relative advantages of the internet of things and hence IoMT as innovations include an increase in efficiency of operation and operational effectiveness (for example lower the costs of operation by using IoMT) and such innovations will be adopted in organisations. The relative advantage of innovation is considered to be one of the best predictors for the adoption of innovation (Lee et al., 2011). However, some researchers did not find relative advantages in influencing the adoption or usage of an IoMT or any other innovation (e.g., Do, 2008). Furthermore, table 2-6 shows that relative advantage has been commonly conceived as an independent variable and in some instances as a dependent variable. However, whether it has a significant relationship with the internet of things is open to question as can be seen from table 2-6.

Table 2-6: Conceptualisation of Relative Advantage

DoI constructs	**Studies remarks Positive**	**Negative**	**No influence**
Relative Advantage	Relative advantage has a positive influence on technology innovation adoption (Johnson et al., a2018; Salem & Hwang, 2016; Al-Jabri & Sohail, 2012). Relative advantage has a significant influence on the intention to use technological innovation (M-Wallet) (Kaur et al., 2020).	Setiowati et al. (2016) and Tehrani & Shirazi (2014) showed that relative advantage has a negative influence on adoption of technology.	Lee (2014) showed that relative advantage has no effect on RFID adoption.

As far as conceptualisation of relative advantage is concerned it can be seen in the literature that it is used as the independent variable (table 2-6) as well as a mediating variable (Ferreira et al., 2014). This shows that there is a lack of consistency in conceptualising relative advantage. This is an important grey area in understanding diffusion. on the one hand, Rogers (2003) argues that the relative advantage of an innovation is a predictor of the rate of adoption of an innovation during diffusion at the same time Ferreira et al. (2013) disagree. There is a need to understand how to operationalise relative advantage which in turn will enable the researcher to determine the nature of the relationship between relative advantage and the interventions.

In addition, literature has shown that relative advantage drives interventions, for instance, perceived usefulness and attitude of adopters of innovation (Ferreira et al., 2013), which could help in supporting healthcare professionals in their continuous intention to use IoMT. Other examples of interventions that could be linked to relative advantage include motivation, training and artificial intelligence awareness (Masocha and Chiwenga, 2020; Lim et al., 2020; Chen, 2019). Further, the literature is not clear on how relative advantage is related to those interventions as there appear to be multiple ways by which such a relationship could be drawn. For instance, the relationship between relative advantage and motivation has been conceptualised as being both positive (Masocha and Chiwenga, 2020) and negative (Çalişkan et al., 2018). Similar relationships need to be unearthed if a theoretical linkage has to be established between relative advantage and the interventions. However, such a conception of relative advantage could be construed as dependent on the context or research topic on which the investigation is being conducted. For instance, motivation was driven by relative advantage as a mediating variable in the research conducted Al-Dhaen et al. (2021). Literature thus offers support to draft in relevant variables that it can drive when the researcher is involved in investigating the diffusion of an innovation. Overall, it can be seen that while investigating the diffusion of IoMT as innovation, leading to the usage of IoMT, it is possible to argue that relative advantage could be brought in as a determinant of the continuous intention of healthcare professionals to use IoMT.

- **Complexity**

During diffusion complexity could be a major factor that could positively or negatively affect the usage or acceptance of an innovation (Sider et al., 2021). Thus, it is important to consider the complexity of innovation without which it would be difficult to determine whether an innovation will go through the full process and end in the usage of that innovation. Zhong et al., (2017) argue that complexities occur when users (for instance healthcare professionals) want to select a product (e.g., wearables) and plan to use it. Examples of complexities could include a lack of skilled workforce to manage the multivendor environment concerning IoT or IoMT adoption and use (Haddud et al., 2017; Lin et al., 2016; Wang & Wang, 2016). Thus, while investigating the core concept of determining the continuous intention of the healthcare professionals to use IoMT during its diffusion, the complexity of IoMT becomes a necessary construct to be used. Although widely construed to be an independent variable that determines the diffusion of an innovation described by the theory of DoI, it can be seen that complexity is also conceived as a mediator in the literature. For instance, Wang and Wang (2012) used complexity as a mediator representing innovation quality. Therefore, it can be concluded that there is no standardised way to conceptualise complexity, as most of the time it is being used as a determinant of user adoption of an innovation (Yoon & Dongsup Lim, 2020; Zhong et al., 2017). As far as the relationship between complexity and usage of IoMT from table 2-7, it can be seen that it is conceptualised in different ways.

Table 2-7: The mediating and mediated variables related to complexity.

DoI constructs	**Studies remarks Positive**	**Negative**	**No influence**

Complexity	• Complexity positively influencing the intention to use mobile learning platforms (Joo et al., 2014) • Complexity has a significant influence on the intention to use technological innovation (M-Wallet) (Kaur et al., 2020).	• According to (Rogers, 2010) that new technology's complexity would hurt its acceptance rate. • Complexity negatively influences IoT adoption (Olushola, 2019). • Complexity is not helpful to IoT adoption, particularly when no trained staff are available in many of the complex conditions (Haddud et al., 2017).	Al-Jabri and Sohail (2012) found that complexity does not influence technology innovation adoption. AlBar and Hoque (2017) as well as Oliveira et al. (2014), indicated that there is no link between the independent variable complexity and the intention to use technology.

Thus, it is reasonable to conclude that conceptualisation of complexity needs to be considered based on the type of IoMT as an innovation, the complexities involved in understanding, selecting and planning to use the IoMT and finally the use of those devices by healthcare professionals. Therefore, determining the continuous intention to use IoMT during its diffusion using complexity as a construct. In such a situation, complexity largely acts as the independent variable. As far as its relationship with other factors is concerned literature shows that complexity is found to be linked to interventions including motivation, training, artificial intelligence and perceived usefulness (Masocha & Chiwenga, 2020; Yoon & Lim, 2020; Mavrogiorgou et al. 2019; Teo, 2009) although there is no clarity on the in the literature on how to operationalise the linkage between complexity and the interventions. For instance, the relationship between complexity and motivation is Masocha and Chiwenga (2020) while Meltzer et al. (2021) found a negative relationship which is a contradiction. This lack of clarity on the nature of the linkage between complexity and other interventions there needs to be investigated to gain a deeper understanding of how the diffusion constructs influence the continuous intention to use IoMT.

- **Compatibility**

This factor is identified as a determinant of the diffusion of innovation in the literature (Lin & Bautistam 2017). Literature shows that compatibility amongst the various IoMT devices like sensors, networks and applications manufactured by different firms needs to be essential lack of which could affect the usage or adoption of IoMT (Haddud et al., 2017; Ng & Wakenshaw, 2017). Thus, it is reasonable to conclude that compatibility has a role in the adoption of an innovation when it is still diffusing. As far as its conceptualisation of compatibility is concerned, literature shows that it is mostly used as an independent variable (Yoon & Lim, 2020) although there is evidence in the literature to show that it has been operated as a mediating variable (Wang & Wang, 2012). Furthermore, compatibility has been argued to be influencing the diffusion of innovations like IoMT during the process of which it interacts with interventions before impacting continuous intention to use IoMT. For instance, literature shows that compatibility is linked to motivation, training, artificial intelligence and perceived ease of use (Masocha & Chiwenga, 2020; Park et al, 2017). However, the nature of the relationship between compatibility and the interventions is not clear in the literature especially when IoMT is diffusing. For instance, Khan et al. (2020) found that compatibility and motivation were positively correlated. However, this implies that when IoMT is incompatible there could be demotivation amongst the users an aspect that appears to be neglected by researchers. Thus, there is a need to know how compatibility interacts with the interventions and identify how the interventions could be operationalized. Furthermore, from table 2-8, it can be seen that compatibility has been conceptualised in various ways.

Table 2-8: Conceptualisations of compatibility found in the literature

DoI constructs	Studies remarks Positive	Negative
Compatibility	● Compatibility is normally positively linked with innovation adoption (Rogers, 2003). ● Compatibility has a significant and positive impact on the behavioural intention to use IoT (Lu, 2021). ● Octavius & Antonio (2021) found that compatibility is also a significant factor in influencing the intention to adopt the mHealth application. ● Compatibility has a significant influence on the intention to use technological innovation (M-Wallet) (Kaur et al., 2020). ● Al-Jabri and Sohail (2012) found that compatibility has a positive influence on technology innovation adoption.	Osorio-Gallego et al. (2016) found that compatibility harms technology innovation (ICT).

Table 2-8. shows that contradictory results have been reported regarding compatibility's influence on the acceptance and use of IoMT. The blurred results are not able to provide conclusively any evidence on how compatibility determines continuous intention to use IoMT. This in turn points towards the need to investigate the influence of compatibility and continuous intention to use IoMT when it is still diffusing. The results of such an investigation could provide the basis to understand how to manipulate the diffusion of IoMT and enable continuous intention to use IoMT.

- **Trialability**

Rogers (2003) argued that innovation needs to be examined before users intend to use it in the environment in which it will be adopted. Such a step provides an opportunity to understand how the innovation performs and its usefulness. For instance, a manufacturer of ECG equipment with remote sensors would like to experiment with how it performs in hospitals when healthcare professionals want to test a patient. Then healthcare professionals would like to try the equipment out to know whether the innovation is worth adopting. Research shows that trialability is usually positively correlated to the intention to use or adapt an innovation (Pashaeypoor et al., 2016; Rogers, 2003). The conceptualisation of trialability is found to be varying in the literature. Table 2-9 provides the various ways trialability has been operationalised by researchers.

Table 2-9: Conceptualisation of trialability

DoI construct s	Studies remarks Positive	Negative	No influence
Trialability	• Al-Jabri and Sohail (2012) found that Relative advantage has a positive influence on the intention to use technology such as Moodle. • Lee et al. (2011) and Lee (2007) showed that trialability had a positive influence on the intention to use technology. • According to Thongkam et al. (2021) trialability has a less substantial positive association with adoption intention to use technology.	• Trialability was found to have a significant impact on adoption, its effect turned out to be a negative influence (Ramayahet al., 2013).	• Trialability has no impact on the users' intentions to adopt IoT Lu (2021). • Johnson et al. (2020) found that trialability does not influence technology innovation adoption. • Kaur et al. (2020) indicated that trialability does not influence technology innovation adoption. • Since trialability and observability are not directly related to the innovation diffusion process they are frequently left out of innovation research (Martins et al., 2016; Oliveira et al., 2014).

It can be seen that while IoMT diffusing, trialability by users assumes significance. However, although literature shows that trialability influences the usage of innovation (Sholahuddin et al., 2019), there are interventions like motivation, perceived attitude and perceived usefulness (Huang et al., 2020; Çalişkan et al. 2018). The relationship between the interventions however is not possible to be determined uniformly across research outcomes. For instance, while Huang et al. (2020) found a positive correlation between trialability and perceived attitude and perceived usefulness, at the same time Çalişkan et al. (2018) found a negative correlation with motivation. This shows that the operation of trialability is not consistent with results found in the literature which points toward contradictory outcomes. The reason for this could be the context in which trialability as a diffusion of innovation construct has been applied. Thus, it is reasonable to conclude that the trialability of IoMT qualifies to be included in the investigation to gain an understanding of its real nature while IoMT is still diffusing.

- **Observability**

Finally, the last factor that is purported to influence the usage of innovation and its diffusion is observability (Rogers, 2003). Observability indicates the level to which the results of an innovation are visible to an adopter like healthcare professionals (Alkhalil et al., 2017; Rogers, 2003). For example, the use of IoMT devices such as IV pumps patient monitors may require demonstration needs to be witnessed by the healthcare professionals. However, such demonstrations may lead to a positive relationship between observability and continuous intention to use by the healthcare professionals if those demonstrations provide an idea about the usefulness of the device for patient care. The demonstration can also lead to a negative relationship if the demonstration of the IoMT device is not well understood by the healthcare professionals with those professionals not being able to accept the product. Thus, observability becomes an important construct that can be used to determine the continuous intention of the healthcare professionals to use IoMT. Furthermore, like the other four constructs of DoI, interventions affect the operationalization of observability (Tran & Cheng, 2017). For instance, in their investigation on the understanding of consumers' intention to use biofuels in Viet Nam, Tran and Cheng (2017) introduced the perceived ease of use and usefulness and attitude as interventions in the path linking observability and intention to use an innovation. Similarly, Lin and Bautista (2017) introduced trialability as an intervention while studying the mobile health literacy of university going students. It can be seen that the introduction of interventions in understanding the determination of continuous intention of the healthcare professionals using observability while gaining currency, at the same time there is a lack of a standard method that could be used to choose and operationalise the intervention. Thus, a need arises to understand how observability can be conceptualised to determine the continuous intention to use IoMT when it is still diffusing. This is a gap in the literature and this research aims to address this gap. As far as the literature is concerned, observability has been conceptualised in various ways and is provided in table 2-10.

Table 2-10: Conceptualisation of observability

DoI constructs	Studies remarks Positive	Negative	No influence
Observability	• Observability significantly influences the intention to adopt the IoT (Lu, 2021). • Al-Jabri and Sohail (2012) found that Relative advantage has a positive influence on technology innovation adoption. • Observability has a significant influence on the intention to use technological innovation (Mobil Wallet) (Kaur et al., 2020) and Mobile learning (Kim & Rha, 2018)	Vitriastuti and Adhiutama's (2019) findings showed that observability has a negative influence on technological innovation	• Thongkam et al. (2021); Kapoor et al. (2013) mentioned in their studies that observability of users' intention to use technology is insignificant. • Since trialability and observability are not directly related to the innovation diffusion process they are frequently left out of innovation research (Martins et al., 2016; Oliveira et al., 2014).

From table 2-10, it can be seen that researchers have conceptualised observability in different ways, largely based on context. This indicates that the concept of observability requires to be understood keeping in view the context and accordingly conceptualised. Further to critically reviewing the literature related to the five factors identified by the theory of DoI, the following section deals with the actual interventions that will be reviewed in this chapter keeping in view the core issue of this research.

2.14.2. Factors related to DoI constructs

In the majority of the research operationalisation of DoI constructs has been one of the independent variables that determine the behavioural intentions of users of technology. For instance, in the research conducted by Al-Rahmi et al. (2019) the five factors of DoI have been used as independent variables to determine the behavioural intention to use the e-learning system. Similarly, in the research conducted by Emani et al. (2018) again, the DoI factors were used as independent variables to understand perceptions of the use of a patient portal by patients. Although similar models exist regarding IoMT (e.g., Salleh & Daud., 2019), an important gap exists is that no research has attempted to understand the combined intervention of motivation to use IoMT and training in IoMT in the relationship between DoI factors and behavioural intention to use IoMT. Lack of understanding of how motivation to use IoMT and training to use IoMT can be related to DoI indicates that the current models cannot explain how to improve the usage of IoMT when behavioural and management attributes are excluded from the investigation. This is a major gap in the research. Further, it can be seen from the research work of Scott et al. (2020) that motivation is another factor that needs to be used to ensure new ideas diffuse for usage, Scott et al. recommend that researchers should be provided with a system design as part of the policy and motivate and provide them with opportunities to develop and commercialise products. It is also argued that innovation and commercialisation should be a priority in organisation. This shows that motivation is a factor that affects innovation. Finally, it is argued in the literature that training is an inseparable concept of motivation (Ozkeser,2019) these two aspects go other. Thus, in any research, that is concerned with the diffusion of innovation of IoMT and uses training or motivation as a factor, then it is important to consider the usability of both training in IoMT and motivation to diffuse innovation or use of IoMT together.

2.14.3. Measurement of DoI factors

DoI factors have been widely measured using measures developed by Moore and Benbasat (1991) using a survey questionnaire. However, over some time, other researchers have also contributed to measuring the five factors through quantitative methods. Each one of the researchers or a group of researchers has developed an instrument based on specific parameters. For instance, Moore and Benbasat (1991) caution and say, “While the various items were developed to be as general as possible, they were worded and tested concerning a particular innovation, the Personal Workstation, in a particular context, organisational work”. This points toward the need to consider these aspects while adapting the instrument developed by Moore and Benbasat (1991) for other research projects. Other researchers who have contributed to instrument development to measure the five factors include Savoury (2019), Al-Rahmi et al. (2019) and Oliveira et al. (2014).

2.15. Motivation to use IoMT

While much has been discussed about the concept of motivation as a concept and its identification as a behavioural attribute of human beings (Maldonado et al. 2019; Peansupap & Walker, 2005), researchers continue to analyse this attribute still, to know how people behave as innovations are brought out in rapid sequence. Motivation is a personal characteristic and has been found to play an important role in many technologies and innovative behavioural intention to use IoMT and usage-related concepts (Marzouki & Belkahla, 2019; Hau & Kang, 2016; Franke et al., 2006). Motivation is shown to be a factor in IoT and IoMT related research, usage of technology-related research, training and learning-related research, and innovation-related research (Baudier et al., 2019; Oesterle et al., 2019; Chakraborty et al., 2019; Padyab et al., 2019). While these examples show that motivation is a major factor in behaviour related research, this section critically reviews the literature to gain knowledge on why it is important to any research related to the usage of or behavioural intention to use IoMT.

2.15.1. Motivation is a concept

Motivation is understood in various ways. Table 2-11. Provides an idea of various thoughts about the concept of motivation.

Table 2-11: Motivation, types, description and context

#	What is motivation and types of motivation	Authors	Context
1	If someone is moved to do something it is called motivation.	Ryan and Deci (2000)	About intrinsic and extrinsic motivation
2	Computer playfulness could be considered as intrinsic motivation related to using any new system.	Venkatesh and Bala (2008)	Implications for managerial decision making on IT implementation in organisations.
3	Intrinsic motivation is a type of autonomous motivation where the motivation lies with the behaviour itself.	Deci et al. (2017)	Study of self-determination theory in organisations.
4	Extrinsic motivation is a cognition (as opposed to emotion) that is related to the benefits of using a system.	Venkatesh and Bala (2008)	Implications for managerial decision making on IT implementation in organisations.
5	Any activity that enables a person to attain a separable consequence, whether tangible or otherwise is called extrinsic motivation and covers all instrumental behaviours.	Deci et al. (2017)	Study of self-determination theory in organisations.

6	Individuals are said to be motivated when those individuals are pushed by their desire to accomplish their psychological and social needs.	Cho et al. (2019)	Study of motivations of social media use and their mediating and moderating roles
7	Autonomous motivation indicates the behaviour of a person who is engaged in an activity with a full sense of willingness, volition, and choice. Often related to intrinsic motivation.	Deci et al. (2017)	Study of self-determination theory in organisations.
8	Controlled motivation involves contingent rewards or power dynamics that impact employees' efforts, generate short-term gains on focused results and produce negative spillover effects on the performance that follows and work engagement. Usually related to extrinsic motivation.	Deci et al. (2017)	Study of self-determination theory in organisations.
9	The innovation-decision process is "an information-seeking and information-processing activity, where an individual is motivated to reduce uncertainty about the advantages and disadvantages of an innovation".	Rogers (2003, p. 172)	Diffusion of innovation theory

Table 2-11. shows that motivation can impact the behaviour of a person in several ways. This is significant because the behaviour of a person concerning motivation has an impact on the outcome of the behaviour of that person. For instance, if an employee is motivated to use IoMT because of a probable reason that using IoMT could make the task easier than before, then that employee is likely to use IoMT (Deci et al., 2017). According to Ryan and Deci (2000), a person could be motivated to undertake an activity because of the potential utility or value, or outcome derived through the activity and enables the person to gain some privileges as a result of completing that activity. This argument then leads to the question of the level of motivation that is needed to motivate a person and the type of motivation (Cano et al., 2021; Ryan & Deci, 2000). So, motivation is seen to be a varying construct that can be dependent on certain other factors at times and a driving factor at some other times. This inference can be appropriate because if a person's level of motivation is high, then the outcome achieved in terms of performance could be high, which indicates that motivation is driving performance. For instance, in the field of healthcare, a professional may be motivated to use IoMT because the facilities offered by the technology can enable the professional to improve the quality of healthcare services (Paul et al., 2021). Especially in cases where the patientcare involves the need to record accurately aspects like a patient's movement and other activities, IoMT could provide support to the healthcare professional to perform the task with easiness as IoMT can collect data automatically through the sensor without any manual intervention, thus reducing the tediousness involved in performing the task if IoMT were not to be used

(Islam et al., 2015). Here motivation drives better performance. On the other hand, learning to use IoMT could enable the professional to provide better healthcare services, if the professional feels that such improved services could yield some reward for instance using best practices in providing healthcare (Zann, 2017). Here reward drives the professional to be motivated. Thus, motivated persons' performance could be enhanced if there is a way to understand the type and level of motivation that influences the person. Although the literature is replete with several publications related to the motivation of people, particularly employees and professionals using IoT (e.g., Baudier et al., 2019; Alliance for Internet of Things Innovation (AIOTI, 2019), yet understanding what type of motivation can motivate people, in what context and to what extent has remained a challenge. For instance, widely used concept of motivation describes intrinsic and extrinsic motivation (Cano et al., 2021). Intrinsic motivation is referred to as the interest a person has in his or her work and demonstrates that he or she plays an active role in the development of their aims or goals and aspirations. Extrinsic motivation is described as the motivation that is demonstrated by a person when influenced by factors outside the realm of a workplace (Cano et al., 2021; p. 4). Example of intrinsic motivation include personal performance, pleasure and satisfaction in performing tasks while an example of an extrinsic motivation could be financial rewards or incentives (Giancola, 2014; Cerasoli et al., 2014; Lin, 2007). One of the most important aspects of motivation is that it shows the direction, intensity and persistence of performance behaviours (Cerasoli et al., 2014). Thus, the concept of motivation becomes important to this research which is concerned with reuse or persistent or continuous intention to use IoMT.

Determining both intrinsic and extrinsic motivation is a challenge. For instance, Linke et al. (2020) found in their study of determining the adapting behaviour of students that intrinsic reward is linked to intrinsic motivation but faced challenges in determining the intrinsic motivation. Similar examples found in the literature show that determining the motivation is an area that needs further research (e.g., Thibaud et al., 2018; Al-Gahtani, 2016). Furthermore, extrinsic and intrinsic motivations are argued to be influencing the intention of workers or their supervisors with regard to specific activities (example usage of IoMT) although not much is known about the factors influencing motivation in regard to the intention of workers or their supervisors (Tűrkeș et al., 2020; Lin, 2007). In addition, literature shows that previous studies have examined only the factors that influence the acceptance of the IoT but not the future use of IoT solutions including those concerned with healthcare (Almetere et al., 2020). Furthermore, the study by Tűrkeș et al. (2020) found that mediating factors (extrinsic motivation factor) affect the relationship between intrinsic motivation and intention of managers to use IoT solutions although their study was not conclusive. This implies that not only motivation as a factor that could determine the future use of IoT in health settings is under researched, even the mediating effect of motivation is also not well understood. Taking the above arguments into account, it can be concluded that there is a need to further understand the impact of motivation as a concept on the continuous intention to use IoMT. To understand this phenomenon, it was necessary to apply relevant theories that explain motivation as a construct. This is discussed next.

2.15.2. Motivation theories

Widely used theories of motivation include the self-determination theory, two-factor theory, Maslow's Hierarchy of Needs, expectancy model and protection motivation model (Oh et al., 2018; Deci et al., 2017; Alshmemri et al., 2017; Haque et al., 2014; Rogers, 2003, p. 172). Amongst the theories used in IoT and IoMT research to explain the concept of motivation is the self-determination theory which has been used by researchers (e.g., Baudier et al. 2019; Pope et al. 2019). Some have used the protection motivation model (e.g., Oh et al., 2018) in studying IoT and some have used DoI theory to explain the diffusion of innovation (Bhat et al., 2021). A search through Google did not reveal the use of any other theories including the two-factor theory, Maslow's Hierarchy of Needs and the expectancy model regarding IoMT research as of date. Taking into account the fact that the protection motivation theory is mostly covering the dangers people face and are motivated to protect themselves (Ifinedo, 2012), the only theories that are left with are the self-determination theory and DoI that have been used in IoT and IoMT research.

2.15.3. Self Determination Theory

Motivation changes behaviour (Stone et al., 2020) Change in behaviour brings challenges, for instance, resistance to change (Stanley et al., 2005). Therefore, how determining motivation, the level of motivation and the type of motivation becomes an important area that concerns researchers who are involved in studying behavioural changes and intentions, related to technology and innovation. Self-determination theory (SDT) is found to be useful in understanding the concept of motivation and is widely used by many researchers concerned with innovation and use of technology like IoMT or any healthcare technological smart devices or systems (e.g., Keenan et al., 2021; Siepmann, & Kowalczuk, 2021; Baudier et al., 2019). According to SDT, the type of motivation an employee has will affect the employee's performance and well-being. In such a situation, SDT posits that types of motivation can be differentiated, and it is possible to see different types of motivation have operationally different catalysts, concomitants and consequences (Deci et al., 2017).

However, there are limitations to the application of SDT. For instance, SDT does not explain why certain times financial rewards can be ineffective and also be detrimental to success and performance quality (e.g., Wunderlich et al., 2013; Boggiano, 1998; Deutsch, 1985; Danner & Lonky, 1981; McGraw, 1978; Pritchard et al., 1977) In this case it can be seen that SDT does not clarify why motivation does not change the behaviour of people. Despite limitations, researchers have applied SDT in studies concerning motivation in different areas including IoT research (e.g., Baudier et al., 2019).

2.15.4. Factors affecting motivation

There are multiple factors that affect motivation. Literature shows that motivation as a construct is influenced by factors including self-healing, self-association, self-design, self-discipline, self-entertainment (Baudier et al., 2019) and perceived locus of causality (PLOC) (Wunderlich et al., 2013; Ryan & Connell, 1989). In addition, if one considers the TAM constructs perceived ease of use and usefulness and behavioural intention to accept technology as representing motivation, then many models show motivation as being determined by all the five constructs of DoI namely relative advantage, compatibility, complexity, trialability and observability. In essence, if the example of the model developed by Al-Rahmi et al. (2019) is taken for analysis, it can be seen that the following factors in the figure 2.8 are related to motivation:

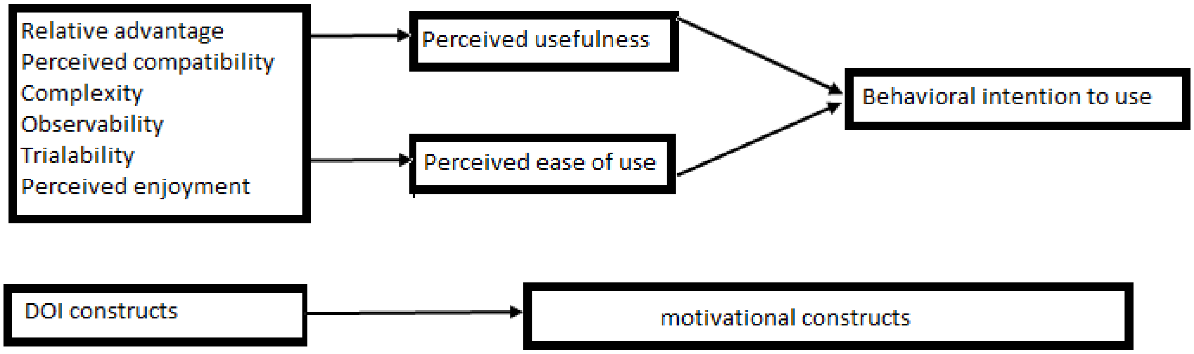


Figure 2.8: Representation of motivational constructs from the model developed by Al-Rahmi et al. (2019).

Furthermore, there is evidence in the literature to show that intrinsic motivation has been used as a determinant of the continuous use of technology (Agrifoglio et al. 2012; Lin & Lu, 2011). Again, literature shows that Deci (1973) has suggested that external events related to behaviour (compatibility) can influence people's intrinsic motivation. Vallerand (1997) echoed similar sentiments and argued that compatibility influences intrinsic motivation. The foregoing arguments provide only partial support to conceptualise motivation. There is a clear dilemma found in the literature on whether to use intrinsic motivation as a determinant or a determined or a mediating or a moderating variable. In the context of this research which is investigating the determination of the central issue of the continuous intention to use IoMT, there is a need to know how motivation to use IoMT could be conceived. This is an important gap in the literature.

2.15.5. Conceptualising motivation

Motivation as a concept has been varyingly conceptualised in the literature. For instance, Moore and Benbasat (2000) argued that motivation is driven by the construct relative advantage depicted in DoI because adopting innovation is argued to lead to social status. The motivation here is deemed to be a dependent variable and innovation (e.g., the relative advantage of the innovation) acts as an independent variable. As a corollary, it can be said that using innovation is motivated because the user thinks it leads to gaining social status. This points toward the relationship between innovation → motivation → and intention to use or reuse an innovation. In another instance, Wunderlich et al. (2013) argue that motivation acts as an endogenous variable in determining the user intentions meaning that motivation is driven by an independent variable which in turn drives user intentions. However, literature shows that there are theories (e.g., expectancy theory (Armstrong, 2006; Vroom, 1964)) that portray motivation as an exogenous variable which triggers behaviour (e.g., Haque et al., 2014; Wunderlich et al., 2013).

Furthermore, in many models found in the literature motivation is found to be a mediating variable. For example, Maldonado et al. (2019) used different types of motivations as a mediating variable between autonomy support and concentration in their study of teacher autonomy support in physical education classes as a determinant of concentration. Baudier et al. (2019) used motivation as a mediating variable in their study of employees incorporates and their acceptance behaviour concerning the healthcare internet of things. Meuter et al. (2005) posited that motivation mediates between innovation factors including relative advantage, compatibility and complexity on the one hand and behavioural intention to use IoMT on the other. However, Meuter et al. consider motivation as a powerful determinant of behavioural intention to use IoMT, implying acceptance or intention to use. These examples amply demonstrate that motivation is conceived as a mediating variable in many studies.

While literature shows that intrinsic and extrinsic motivation can act as both endogenous and exogenous variables, conceptualising the construct depends on the research context. In practical terms, it can be seen that computer playfulness (enjoyable experience) is considered to be an example of intrinsic motivation that is linked to the usage of any new system while perceived usefulness is an example of extrinsic motivation (Venkatesh & Bala, 2008). When applied to the concept of usage of IoMT it can be seen that usage of this innovation will occur if users are motivated due to the enjoyable experience those users can have while using the innovation. Similarly using IoMT must be perceived by the users to be useful which in turn could influence their behavioural intention to use IoMT. These contrasting situations may make one feel that intrinsic and extrinsic motivation are different constructs but in reality, it is seen that the two complement each other (Wunderlich et al., 2013). Further to determining the gap in the literature concerning the conceptualisation of motivation to use IoMT, the next section deals with the measurement of motivation as a construct without which it will be difficult to understand the concept.

2.15.6. Measurement of motivation

Motivation is measured in the literature by researchers in different ways. For instance, Lai (2011) claims that most of the time motivation is measured using self-reported measures or rating scales. Many such measuring instruments are available in the literature including the Harter's Scale of Intrinsic Versus Extrinsic Motivational Orientation in the Classroom (1981), the Children's Academic Intrinsic Motivation Inventory (Gottfried, 1986), the Instrumental Competence Scale for Children (Lange & MacKinnon, 1987) and the motivation scale developed by Guay et al. (2000). Each scale has been developed for measuring motivation in a particular context. This also throws up a challenge if one wants to adopt a particular scale for a research project as multiple scales provide a divergent set of measuring scales and adapting them could be a tedious and confusing aspect. Having discussed the concept of motivation, to use the conceptualisation in this research there was a necessity to apply theories to support the conceptualisation. Thus, the next section discusses the theories that could be used to support the conceptualisation.

2.16. Training to use IoMT

Internet of things (IoT) is a complex technological innovation. An example of IoT could be interconnections between sensors, measuring such physiological parameters as ECG, blood pressure, blood oxygen saturation, pedometers, gyroscopes, GPS, relative air humidity and temperature (Rubí & Gondim, 2019). Such sensors when connected, through the internet and computer networks, then the resulting product is a complex network of interoperable devices, operating which could be a very challenging task. Literature shows that using and maintaining IoT invariably requires training (Boyarchuk et al., 2019; Nagy et al., 2018; Fathema et al., 2015). Especially in the field of healthcare, the problem of lack of training in IoT could be a major challenge (Dang et al., 2019). For instance, reprogramming the software and hardware of devices connected to the internet of things which cannot be done without training could be a challenge. Lack of trained manpower could be a serious issue in operating the IoT. Similarly, there is a need to train those who need healthcare to make them know how to use IoT (Nagy et al., 2018). For instance, medical professionals find educating and training patients to capture data about their health essential (Nagy et al., 2018). Besides training of smart digital devices such

IoMT, AI and ehealth is essential and demanded even in university's education to be taught in their programs and curriculums to enable medical students to utilise from training sessions during their medical practice and before they get hired and join as healthcare professionals (Linderman et al., 2020; Echelard et al., 2020)

However, an important fact that needs to be borne in mind is that wherever there is a change in technology or new technology is introduced or diffusing, the concept of training comes into the picture. Further training as a factor is affected by a variety of challenges including problems related to preparing an appropriate curriculum, resistance to learning, problems related to the design of the training depending on functionality, problems in training need analysis, lack of appropriate learning resources, infrastructure, the time factor, retraining, problems in getting qualified trainers and funds (Kharchenko, 2019; Shashank, 2017; D'Agostino et al., 2015; Liddell et al., 2008). These challenges cannot be ruled out while providing training and implementing an innovation like IoT especially when it is diffusing. In addition, continuous intention to use IoMT or a technological innovation including IoT can simply depend on the support available to the users and patients of IoMT and IoT which for the most part implies training and maintenance, considered as enablers of continuous intention to use IoMT or IoT (Otaibi, 2019). While it is seen in the literature that training could be a major barrier to the intention to use IoMT or IoT, solutions to overcome the barriers using training in IoMT and IoT have not yet been fully developed by researchers (Türkes et al., 2019). For instance, the literature highlights that if training and retraining of patients and service providers are not effective concering using IoT, then there will be a serious concern about the utility of the technology to improve patient care (World Economic Forum, 2019; Fawaz & Shin, 2019; Dang et al., 2019; Dauwed et al., 2018; OECD, 2016).

When viewed from another perspective related to training in IoT and IoMT, and continuous intention to use IoMT or IoT, a major concern that needs to be addressed is the challenges that impede the intention to use IoMT. For instance, there are many types of IoT devices including music streaming, digital pen, key finder, smart bulb, glucose monitors, smart bands, activity trackers, headsets, heart-rate monitors and smart thermos. Operating such IoT devices individually and concurrently requires training (Otaibi, 2019; Fawaz & Shin, 2019). The reason for this is that each one of these devices could be manufactured by different firms, with each of those devices having its specifications and operating procedures. In such a situation it is quite possible that training and retraining becomes a major challenge as multiple firms are involved and learning those concepts that help in gaining knowledge on how to operate each one of those devices concurrently and in a network could be a challenge (World Economic Forum, 2019; Durodolu, 2016). There are additional challenges related to training that arise while one discusses training users in technological innovations which include challenges related to designing, delivery, evaluation, effectiveness, trainer attributes and outcomes related to training programmes (Alias et al., 2019; Aguinis & Kraiger, 2009). Such challenges have the potential to turn away users leading to intentional refusal to use IoMT or IoT. The foregoing discussions point out that challenges in the context of IoMT continue to exist and those challenges need to be addressed through research to bring out solutions that can to some extent alleviate the impact of those challenges.

The various ways by which training is provided to users and technicians currently include apprenticeships, industry attachments, on the job training or in-service training, work-based learning (WBL) (Bahl & Dietzen, 2019) workshops (Boyarchuk et al., 2019), face to face interactions, e-learning (Abdullah & Ward, 2016; Fathema et al., 2015; Cheung & Vogel, 2013), mobile learning (Abdullah &Ward, 2016; Cheon et al., 2012; Iqbal & Qureshi, 2012) and computer-based learning (Wang et al., 2018). These methods require different abilities on the part of the users of IoT to adapt and get trained through a particular training method. Lack of ability on the part of trainers as well as users of IoT and IoMT to get trained can lead to possible challenges in acquiring knowledge on the intention to use IoMT or IoT during training. Thus, it can be seen that training and getting trained could be major constraints for many including the patients due in part to the complex steps involved in the training process and sometimes the contents of training that could be overwhelming. In addition, other aspects including the attitude of the learners and trainers, facilitating conditions and quality problems could contribute to poor learning (Wang et al., 2018) and hence resistance to adopting a technology including IoT becomes a challenge. Thus, an overall assessment of the IoT devices, their interconnections, user training needs and methods used for training show that training is a major challenge and continues to plague continuous intention to use IoMT of IoT.

It is also seen that training and its influence on the intention to use an innovation can be supported by the Theory of Planned Behaviour (Ajzen, 1991). For instance, Herrmann and Kim (2017) argue that TPB is a suitable theory to use to comprehend technology and health behaviours. According to TPB behaviour is influenced by behavioural beliefs and perceptions and such perceptions are linked to positive and negative outcomes obtained through the behaviour which leads to those beliefs (Ajzen, 1990). Furthermore, the components of TPB attitude, perceived control, subjective norms and behavioural intention (Ajzen, 1991) have been used by researchers to explain the intention to use technology, for instance, e-learning continuing medical education (e-CME) (Hadadgar et al., 2016). While the theory can be used to relate training (for instance medical education) to intention to use, at the same time it may have limitations to integrate DoI factors. For instance, Al-Rahmi et al., (2019) argue that the four variables of TPB namely attitudes, subjective norms, perceived behavioural control, and intentions (Lo et al., 2019) can be considered equivalent to relative advantage, compatibility, trialability and observability. This shows that complexity cannot be considered equivalent to any variable in TPB. Despite this limitation, TPB finds application in explaining the relationship between training and intention to use an innovation.

Although other theories that have been mentioned above have not been discussed in this section, it can be seen that since this research is focusing on IoT, a technology that is considered to be diffusing still, the most appropriate of the theories is DoI was found to be necessary to be discussed. The other theories like TAM, UTAUT, Motivational Model and PZB model (Tan, 2019; Tan & Tsu, 2017) have not been discussed as they are not concerned with user training unlike DoI and TPB but more concerned with factors including the intention to adopt, motivation and service quality. Further to discussing the different theories that could be used to explain the concept of training users and its relationship to behavioural intention to use IoMT of IoT, it is important to conceptualise training of users.

2.16.1. Conceptualisation of training to use IoMT as a variable

From the previous sections it is fairly clear that training of users of IoT has been seen to be an important factor that affects continuous intention that is continuous intention to use

IoMT of IoT. It is further seen that training to use IoMT is a complex factor, knowledge about which can enable an understanding of its role in continuous or continuous intention to use IoMT or non-continuous intention to use IoMT (Saarikko et al., 2017). Training as a factor is seen to be a quantity that manifests in different forms (e.g. apprenticeships, industry attachments, on the job training or in-service training, work-based learning (WBL), face to face interactions, e-learning, mobile learning and computer-based learning) (Billett et al., 2021; El-Ashmawi et al., 2017; Zhao & Shen, 2019) which either encourage or discourage users in their intention to adopt IoT (Martin, 2021). In addition, training is required to use various IoT devices, and such training is specific to each device meaning that if training is not provided to the users in using each one of the devices, then using or adopting IoT by users may be a concern. These aspects indicate that training to use IoT can be conceived as a variable and determinant that could be related to continuous intention to use IoMT by users although such an argument needs to be tested using empirical research, as no research seems to have linked training to use IoT or IoMT as a concept to continuous intention to use IoMT (Yousef et al., 2021).

Further to conceptualising training to use IoMT as a determinant of continuous intention to use IoMT when it is still diffusing, it is necessary to understand whether training to use any technology is driven by other factors. There is evidence to show that DoI factors influence training to use innovation as a dependent variable for instance the research conducted by Mairura (2016) showed that the relative advantage of innovation can be linked to training. This implies that on the one hand training to use IoMT could be used as a driver of continuous intention to use IoMT, on the other, it can be conceptualised as a dependent variable driven by other factors including the DoI factors. Thus, while testing the relationship between factors that determine continuous intention to use IoMT and continuous intention to use IoMT, training to use IoMT if involved needs to be conceived appropriately. For instance, from the discussion given above it can be seen that training to use IoMT could be used as an independent variable driving continuous intention to use IoMT based on the argument of Venkatesh et al. (2012) or as mediating variable between an independent variable (e.g., DoI factors) and a dependent variable (e.g., continuous intention to use IoMT). Either conceptualisation is sparsely used by researchers in the extant literature but in the context of IoMT which is still diffusing, there is hardly any research that has conceptualized training to use IoMT in a particular configuration including as a mediator. Further to reviewing the conceptualisation of training to use IoMT it is necessary to understand how to measure it.

Training as a concept has been empirically measured by different researchers (Alias et al., 2019; Rea, 2004; Simonsen & Reyes, 2003; Lee & Pershing, 2002; Morgan & Casper, 2000; Tracey et al., 1995). Training as a concept is measured by different researchers in different ways. For instance, Alias et al., (2019) used training content, method, competency and effectiveness to measure training. But Rea (2004), Lee and Pershing (2002), Morgan and Casper (2000) and Tracey et al. (1995) used intention to transfer learning as a factor to measure training. Again, Rae (2004), Simonsen and Reyes (2003), Towler and Dipboye (2001), Morgan and Casper (2000), Burke and Baldwin (1999), Olson (1994) and Knowles (1980) used trainer performance and behaviour as a factor to measure training. Thus, it can be seen that in the literature training as a concept has been measured in various ways using various instruments by researchers and those instruments have been validated. The inference that can be derived is that training as a concept can be measured quantitatively. However, it must be highlighted here at this point that there are multiple ways to measure training as a quantity and it is not clear whether there can be one measuring method that can override all others, thus becoming universal. The lack of consensus amongst researchers on one particular method that could be used universally to measure training is a major concern that leads to a lack of clarity in choosing one method to measure training. After discussing the various ways by which training could be measured, it was essential now to know whether other factors need to be considered alongside training as a concept while discussing the continuous intention to use IoMT.

2.16.2. Relationship between training to use IoMT and other factors

From the literature it can be seen that other factors could come into play while training to use IoMT is discussed as a determinant of continuous intention to use IoMT by users. For instance, literature shows that motivation is an important ally of training (Bhatti et al., 2014). Motivation to learn is considered to be an important factor that is discussed in the literature as linked to training. Similarly, DoI components namely relative advantage, compatibility, complexity, trialability and observability have been identified as factors that affect training in the literature. For instance (Lewis, 2019) argues that innovation requires training before behavioural intention to use IoMT. These arguments show that innovation, motivation, training, and behavioural intention to use IoMT IoT are interlinked but such a linkage is not understood well due to which it is not possible to exploit the advantages of IoMT. Furthermore, it is hard to come across any research that has investigated the use of DoI constructs as determinants of training, alongside other constructs like motivation in one research (AlQudah et al., 2021). This is a major gap in the literature. After discussing the two important behavioural attributes of healthcare professionals namely motivation and training to use IoMT as mediators with regard to their continuous intention to use IoMT, the review focuses on the importance of other factors that could influence the relationship between motivation and training to use IoMT on the one hand and continuous intention to use IoMT.

2.17. Importance of moderators

From earlier discussions (see section 2.6.6), it can be seen that moderators have an important role in explaining the diffusion of IoMT. This section reviews the literature related to three moderators namely the age of the user of IoMT, novelty-seeking behaviour of the user and the awareness of the user about AI that has implications for the understanding of the continuous intention to use IoMT. Each one of them is discussed next.

2.17.1. Age

Age of the users is shown in the literature to be a major contributor to the understanding of the behavioural intention to use the technology of people (Martins et al., 2018). However, the influence of age is considered to be a moderator in the behavioural intention literature (Venkatesh et al. 2012). While age is considered to be a moderator in both TAM and UTAUT, it is not known how age will influence the relationship between antecedents of continuous intention to use behaviour of users of IoMT. For instance, Venkatesh et al. (2012) have argued that age could be a moderator of the relationship between hedonic motivation and intention to use a technology an argument that may not be generalisable.

Venkatesh et al. (2016) argue that moderators of the relationship between antecedents of intention to use and intention to use may vary according to settings. For example, Gupta et al. (2008) used UTAUT with one moderator that is gender while investigating e-government adoption in a developing country. Age was not considered as a moderator. However, Martins et al. (2018) found age as an important moderator of the relationship between hedonic motivation and intention to use technology and suggest the necessity to investigate the moderating effect of age in varying technological contexts. This is a gap in the literature that needs to be investigated. IoMT being a new technological innovation, it is worthwhile to investigate the moderating effect of age in any model that is studying continuous intention to use IoMT as the use of IoMT spreads across different age groups include naïve technology users. Theoretical support for using age as a variable in models concerned with continuous usage of technology is provided by both TAM and UTAUT. Measurement of age has been dealt with widely in the literature as a demographic factor.

2.17.2. Novelty seeking

As far back as 1983, (Rogers ,1983) identified novelty-seeking behaviour as an important concept that is associated with innovation. It was defined as the extent to which a person accepts new ideas leading to making individual innovation-decision independently of others' experiences. Hirschman (1980) said novelty is the existence of a natural drive or power of motivation in a person that stimulates the person to seek new information. In the field of technology others (Dabholkar & Bagozzi, 2002; Hirschman, 1980; Midgley & Dowling, 1978) have identified novelty-seeking behaviour as an intrinsic motivation to use technology-based products and look for new stimuli. Varying definitions also show a lack of consensus on the understanding of the concept of novelty-seeking.

Literature shows that novelty-seeking behaviour has been used as a construct in different fields including hospitality (Hsiao & Yang, 2010) and mobile banking (Babić-Hodović & Arslanagić-Kalajdžić, 2019). However, as construct it has been used as a moderator (e.g., diffusion success) (Green & Hevner, 2010) as well as a determinant of attitude toward technology (e.g., Babić-Hodović & Arslanagić-Kalajdžić, 2019). Extending these arguments to understand the continuous use of IoMT, it is possible to conclude that there is no clarity on how novelty-seeking behaviour of users of IoMT could be applied to explain the relationship between continuous intention to use IoMT and its antecedents. However, based on the arguments of (Dabholkar & Bagozzi, 2002) who used novelty-seeking behaviour as a moderator while investigating the concept of intention to use technology-based self-services and Babić-Hodović and Arslanagić-Kalajdžić (2019) who used novelty-seeking behaviour as a moderator in studying the attitude of consumers towards mobile banking it is possible to conclude that using novelty seeking as a moderator of the relationship between continuous use of IoMT and its antecedents, a conceptualisation not found in the literature. As far as theoretical support for such a conceptualisation is concerned, researchers have commonly used technology acceptance models including TAM, TPB and DoI to understand the influence of novelty-seeking behaviour on the attitude of the consumers towards technology and consumers' intention to use technology. Thus, it can be argued that in the context of understanding the continuous intention to use IoMT which is still diffusing across many contexts, those theories could be applied. Novelty seeking behaviour has been measured by researchers using the Likert scale (e.g., Sugandini et al. 2018; Dabholkar & Bagozzi, 2002). Thus novelty-seeking behaviour could be measured based on already existing instruments.

2.17.3. Artificial Intelligence (AI) Awareness

Literature shows that Artificial Intelligence (AI) is one of the main enabling technologies (Chen, 2019) AI is playing a major role in the healthcare sector (Arab Health, 2019) AI is turning out to be an important innovation that is promising to change the way the people view things with AI currently flourishing in many industries including healthcare (Chen, 2019; CAICT and Gartner, 2018). In addition to monitoring some diseases companies have brought out IoT based solutions that use more advanced technology based on machine learning which is an off shoot of artificial intelligence. For example, the company Apple has created a smartwatch based on artificial intelligence and machine learning which detects the level of depression and saves it in the cloud.

However, awareness about AI as innovation is still percolating amongst the people and concerns have been raised about its trustworthiness for use in applications (Ashoori & Weisz, 2019). This argument indicates that every innovation may have advantages and disadvantages that need to be considered before use. This applies to AI also as many concerns about AI have been raised already by many researchers for instance decision stakes, decision authority, model trainer, model interpretability, social transparency, and model confidence, predictability, reliability, safety, and efficiency of AI-based decisions and others including fidelity, loyalty, reliability, security, integrity, and familiarity (Ashoori & Weisz, 2019; Cahour & Forzy, 2009; Jian et al., 2000). To overcome concerns, researchers have suggested that awareness about innovations and training in those innovations including AI (Chen, 2019; Mansour et al., 2019) must be provided to users although it was not clear whether awareness about AI and training alone can remove the vulnerabilities in using AI. In this situation, this research chose awareness about AI as the moderating variable that affects AI as an innovation at the beginning stage of diffusion of innovation itself. Already training in IoMT has been identified as an important intervening variable in this research that could influence the relationship between diffusion of innovation and continuous intention to use IoMT.

While innovations are being brought out in rapid succession, the usage of those innovations can be explained by the diffusion of innovation theory. According to DoI theory, awareness of innovation is the first step in the process of diffusion and usage of technology (Leal & Albertin, 2015). This argument could be applied to IoMT which uses AI. Applying the concept of awareness of AI to the relationship between diffusion of innovation factors and continuous intention to the usage of IoMT, it was found that awareness about AI used in IoMT could be used as a construct that could moderate the relationship. The moderating function of awareness as a variable in models dealing with the intention to use technology is mostly found in models that have used UTAUT (Abubakar & Ahmad, 2013; Wu et al., 2012). A close search in the literature review shows that moderating effect of awareness about IoMT on the relationship between the five factors of DoI and the continuous intention to use IoMT is hardly discussed. This lack of knowledge points to the existence of a gap in the literature without whose knowledge it is difficult to manipulate the determinants of continuous intention use IoM. This research develops a conceptualisation which will be tested further. As far as theoretical considerations are concerned, it can be seen that DoI, UTAUT and TAM support the conceptualisation. Finally, awareness of AI could be measured by adapting the survey developed by other researchers (e.g., Gillihan & Ferguson, 2018; Al-Husein & Said, 2015).

2.18. Gaps in the literature and the problems they cause

The main gaps found in the literature concerning the central concern of this research, namely the determination of the influence of concurrent diffusion of innovations on continuous intention to use, are provided below. These gaps provide the basis for formulating the problem statement and research questions. There is a lack of understanding of the relationship between the DOI factors and the continuous intention to use AI-based IoMT. It is further seen that the literature is silent on how to determine and improve the continuous usage of IoMT when both the innovations namely AI and IoMT are concurrently diffusing. Furthermore, problems concerning the effect of an intervention on the relationship between the DOI factors and continuous intention to use. The problems that emerged included

- lack of knowledge on how to determine and encourage healthcare professionals to continue their intention to use IoMT. This has resulted in problems like dilemmas in the minds of healthcare professionals on whether to continue to use a particular innovation that is still diffusing as well as healthcare organisations regarding investing in innovations.
- lack of knowledge on how motivation, training in IoMT, novelty-seeking behaviour of healthcare professionals, age and AI awareness can affect the relationship between DOI factors and continuous intention to use IoMT. This has resulted in a problem for innovators and the IoMT device manufacturing industries do not know how to promote and encourage the adoption and continuation of their innovations and products respectively.
- lack of understanding of how the two innovations namely IoMT and AI diffuse concurrently and influence the continuous intention to use IoMT. This has led to the healthcare professionals not knowing how to effectively use advantages provided by the two innovations.

The gaps in the literature and problems caused by those gaps are dealt with in the following chapter.

2.19. Chapter summary

This literature review has comprehensively and critically discussed the concepts of telemedicine, IoMT, usage of IoMT synonymously used with the phrase behavioural intention to use or continuous intention to use IoMT, DoI factors relative advantage, compatibility, complexity, observability, trialability, motivation to use IoMT and training in IoMT. Additionally, the review has critically looked at moderators of the relationships between DoI factors and training of users of IoMT on the one hand and (training of users, motivation to use IoMT) → continuous intention to use IoMT on the other, which may have a role in determining the influence of DoI factors on continuous intention to use IoMT. The research gaps have been identified. Various theories that could be used to explain many relationships that have emerged have been reviewed critically for application in the research. The conceptualisation of the constructs provides an understanding on how to visualise the variables. This chapter sets the basis for developing the theoretical framework discussed in the next chapter.

3. Chapter 3: Conceptual Framework

3.1. Introduction

This chapter deals with the theoretical framework that was developed to answer the research questions set for this research and fill the research gap identified through the literature review. The research questions were set based on gaps in the literature. Answering the questions led the researcher to investigate the central research issue which is the relationship between the diffusion of AI-based IoMT and continuous intention to use IoMT. In addition, behavioural attributes of the healthcare professionals regarding their intention to use IoMT continuously were found to have some influence on the relationship. Further concepts like continuous intention to use IoMT as an innovation and the perceived characteristics of the innovation AI-based IoMT have remained complex issues. The level of complexity increases further as AI-based IoMT is still diffusing. Taking into account these aspects this theoretical framework has attempted to provide a solution to untangle the complexity associated with the concepts of diffusion of AI-based IoMT, continuous intention to use AI-based IoMT and the behavioural attributes. Further, it provides a way to understand and determine the continuous intention to use AI-based IoMT using diffusion of innovation theory as the basis and other relevant behavioural theories.

3.2. Importance of Diffusion of Innovation theory

Diffusion of Innovation theory suggests that we should intend to use AI-based IoMT continuously by healthcare professionals when AI-based IoMT is still diffusing. Therefore, the investigation begins with taking diffusion as the basic concept that could lead the investigation further. Its ability to explain how innovations diffuse at the individual or organizational level and how it relates to various technical innovations has been discussed in prior studies. The theoretical foundation for the DOI has been developed through a number of studies on the topic of diffusion and innovation which points towards the continuous evolution of DOI. Extending these arguments, it was possible to posit that

AI-based IoMT is considered to be a technological innovation that can be explained by the diffusion of innovation hypothesis an argument that is based on similar arguments provided by Walker (1999). The objective of DOI theory is to comprehend how a useful innovation might spread or diffuse quickly (Lien and Jiang, 2017). According to Rogers (2003), there are five innovative characteristics that are key predictors of technology adoption and diffusion as seen by the members of a social system. Rogers proposed that the five factors which influence whether an innovation will be accepted and spread from person to person are relative advantage, compatibility, complexity, trialability, and observability. Furthermore, Rogers (2003) argued that perceptions of an innovation's perceived features (relative advantage, compatibility, complexity, trialability and observability) influence whether an organization decides to embrace or reject the innovation where factors could account for 49–87% of innovation uptake in both individuals and organizations (Savoury, 2019; Rogers, 2003). These two arguments clearly point out that DOI theory can explain the final usage behaviour of individuals as well as organisations with regard to innovation and its diffusion. Thus, the research uses DOI as the basic theory and applies it to understand how the DOI factors can explain the continuous intention to use IoMT. In addition to DOI, the effect of the behavioural factors on the relationship between DOI factors and continuous intention to use IoMT also necessitated the involvement of DOI with other theories, in particular behavioural theories. Here also the importance of DOI becomes evident. Thus, in order to study both the individual level attribute of continuous intention to use AI-based IoMT and the organisational behaviour employing those individuals this study investigates using the DOI theory as the dominant theory. This also led the researcher to use the diffusion factors namely relative advantage, complexity, compatibility, trialability and observability to be the focus of this research.

3.3. The basic relationships that are under investigation

3.3.1. Factors affecting continuous intention to use IoMT (usage of IoMT)

Continuous intention of users of new technology or innovation including IoMT, and their perception of the innovation called IoMT are complex issues (section 2.6.4). Right from the innovators attempting to bring in IoMT as an innovation to its continued use by the end-user challenges have been found at various levels (Chapter 2). The focus is on how to improve the continuous usage of IoMT. From the literature review, two sets of factors have been identified as affecting the continuous usage or continuous intention to use IoMT. The first set of factors is the diffusion factors. Literature shows that the perception of the relative advantage of IoMT, the compatibility of the devices of IoMT, the complexity of the technology used behind the devices, the observability of IoMT and the trialability of IoMT were to be tested to see whether they have any influence on the continuous intention to use IoMT or not (section 2.14). There are arguments for and against the possibility of diffusion of IoMT amongst the users of IoMT. For instance, Yeh (2020) showed that the five factors of DOI as influencing the continuous intention to use technology directly. The second set of factors included the mediating and moderators that were conceived as intervention factors. This was established by Al-Rahmi et al. (2019) who used the five factors defined by DOI to study the effect of the intervening factors namely perceived usefulness and perceived ease of use of technology on the continuous intention to use technology. The moderator factors Here it must be mentioned that usage implies continued intention to use following the first use of technology and maintain such usage of technology (Pang et al., 2020).

3.3.2. Relationship between DOI factors and continuous intention to use IoMT

This relationship has been used by many researchers to test the utility of the five diffusion factors namely relative advantage, compatibility, complexity, observability and trialability of the innovation in determining the behavioral continuous intention to use IoMT or intention to use innovation (e.g., Yeh, 2020; Ahmad et al., 2018; Lee et al., 2011). Furthermore, some authors have used only select DOI factors to determine behavioural intention or continuous intention to use IoMT of innovation. For instance, Karahoca et al. (2017) used only trialability and compatibility out of the five diffusions of innovation factors to determine the intention to adopt the internet of things in healthcare by individuals. However, the model used by Karahoca et al. (2017) combines Innovation Diffusion Theory, TAM and protection motivation theory to study the IoT behavioural intention to use IoMT intention of individuals. Similarly, Prause (2019) studied the behavioural intention to use IoMT of Industry 4.0 standards in the industry by using three factors of

DOI namely relative advantage, compatibility and complexity which were directly linked to behavioural intention to use IoMT of Industry 4.0 standards. Again, Prause combined other factors to study the combined effect of those factors on behavioural intention to use IoMT behaviour and not just DOI factors. These arguments show that literature is strewn with mixed research concepts concerning using DOI factors in conceptual models.

Actual examples of how researchers have linked each one of the five factors of diffusion to IoMT diffusion are provided in table 3-1.

Table 3-1: Actual examples of the DOI factors relevant to IoMT (Savoury, 2019)

No	Construct	Actual example of the construct	Author/s
1	Relative advantage of IoMT	Increase in efficiencies	Tu (2018); Rymaszewska et al. (2017); Oliveira et al. (2014)
2	Compatibility of IoMT	Compatibility among sensors, networks, and application from different vendors	Haddud et al. (2017); Ng and Wakenshaw (2017)
3	Complexity of IoMT	Lack of skilled staff to manage a multivendor environment	Haddud et al. (2017); Lin et al. (2016); Wang and Wang (2016)
4	Observability of IoMT	Benefits of IoMT are easily demonstrable and removes uncertainty	McMullen et al. (2015)
5	Trialability of IoMT	Conducting limited trials of IoMT to figure out its feasibility and distinguish reality from hype	Shin and Park (2017); Hsu and Yeh (2016)

Next, the theoretical support for establishing the relationship between the five factors and continuous intention to use IoMT can be provided by the theory of DOI. According to the theory if the innovator and the user perceive that IoMT as an innovation provides a relative advantage (the degree to which IoMT as innovation is perceived as being better than its precursor (Venkatesh et al., 2003) over any previous method of collecting and analysing data, then it could lead to the user intending to use IoMT (Rogers, 2003). If there is no relative advantage the users could abandon IoMT. Similarly, if the innovator and the users feel that IoMT is compatible (the degree to which IoMT as innovation is perceived as being consistent with the existing values, needs, and past experiences of potential adopters), less complex (the degree to which IoMT as innovation is perceived as being difficult to use), observable (the degree to which the results of IoMT as innovation are observable to others) and available (the degree to which IoMT as an innovation may be experimented with before behavioural intention to use IoMT) then users are likely to intend to use IoMT (based on Rogers, 2003). However, from the time the innovator has conceived the innovation, till there is a large-scale diffusion of IoMT that is used in a sustainable, manner, it cannot be concluded that the innovation itself is successful.

3.3.3. Relationship between DOI factors, intrinsic motivation and training to use IoMT

From the literature review (section 2.15), it can be seen that motivation is an aspect that determines continuous intention to use innovation and it can be seen that motivation as a concept is driven by the perception of the features of the actual innovation, which is determined by the 5 DOI factors. Conceptualising the five factors of DOI as determinants of motivation (intrinsic or extrinsic) to use IoMT is rarely found in the literature although some supporting evidence is available. For instance, the publications of Al-Rahmi et al. (2019) and Baudier et al. (2019) have brought out the importance of motivation as a mediating construct between diffusion of innovation and continuous intention to use innovation.

Literature also shows that the concept of motivation can be represented by various other components including self-determination, a concept supported by self-determination theory (see section 2.15.3). The theory says “that individuals feel a basic need for autonomy, which is satisfied if they consider that they have the choice to be engaged or not (Deci & Ryan, 2000; Baudier et al., 2019; p. 93). For instance, if technology like IoMT is perceived to be useful and easy to use, then most often users will intend to use IoMT with a sense of autonomy. Thus, motivation as a construct could be studied with the application of self-determination theory.

Furthermore, motivation is associated with training in the literature as a concept that implies that training and motivation could operate together (Olmedo-Moreno et al., 2021; Vanthournout et al., 2015) and hence the relationship between the DOI factors and training to use IoMT needs to be understood. Literature shows that the training of users is identified as an important construct that benefits users of innovations while using those innovations (Al-Gahtani, 2016). According to Venkatesh and Bala (2008) training is an important intervention that that might contribute to the acceptance and usage of technology. The theory of DOI and TPB provides the basis to explain the use of training to use IoMT. TPB posits that users’ behaviour is influenced by their intention to behave where the intention is influenced by attitude, subjective norms, and perceptions of behavioural control (Septiani & Ridlwan, 2020). It is commonly utilised to anticipate intention and behaviour in the context of technology adoption in the medical field (Bronfman et al., 2021; Hennings & Herstatt, 2019; Ifinedo, 2018).

3.3.4. Relationship between the relative advantage of IoMT and motivation to use IoMT

Relative advantage refers to the degree of perceived superiority and usefulness of new and current technologies (Rogers, 2003). IoMT promises plenty of advantages for optimizing and improving healthcare delivery (Kelly et al., 2020). Some of the advantages of IoMT devices include connectivity, networking, and communication protocols (Kelly et al., 2020). The following arguments can be made using DOI to demonstrate the relationship between the relative advantage of IoMT and an individual's intrinsic motivation to utilise it. Individuals' intrinsic desire to utilise IoMT is influenced by the relative advantage of IoMT as innovation, which gives them a sense of autonomy (Jaleel et al. 2020). From a practical standpoint, if a wearable device that monitors a person's diverse actions allows the user to be independent and efficient, the user seems to be intrinsically driven. Furthermore, Saarikko et al. (2020) claim that practical advantages and answers to everyday problems (relative advantage) are critical for IoMT to be used.

Applying the self-determination theory to the relationship between the relative advantage of IoMT and the intrinsic motivation of an individual to use IoMT the following arguments can be posited. Relative advantage of IoMT as innovation creates a sense of autonomy in an individual and influences the intrinsic motivation of individuals to use IoMT. However, to what extent relative advantage exerts pressure on the motivation of users of IoMT needs to be tested using an empirical relationship between relative advantage and motivation of users of IoMT as this aspect is not well understood in the literature (chapter 2). Thus, it is possible to posit the relative advantage of IoMT → motivation to use IoMT. The hypothesis that could be postulated is:

H1a: Relative advantage of IoMT positively influences the motivation of users to use IoMT.

Similarly, as far as training of users in IoMT is concerned it can be seen that literature shows that the relative advantage of IoMT influences training as a construct. This is discussed next.

3.3.5. Relationship between the relative advantage of IoMT and training of users of IoMT

Technological advancements establish the need for healthcare organisations to embrace systems such as IoMT to improve service delivery. However, there is a need to link the benefits of the technology and the ability of users to utilise the IoMT (Emon et al., 2018). Studies indicate that IoMT users are more likely to train on the utilization of the innovation if its relative advantages are apparent. Joyia et al. (2017) investigated the advantages of IoMT and described the benefits that the use of IoMT accords to users. Therefore (European Commission, 2020) pointed out that healthcare's digital transformation is a difficult shift process that will drastically affect the duties of healthcare workers. Until now, the transformation progress has been slower than expected, although COVID-19 has forced the entire world to embrace and use technology (Zalat et al., 2021). However, many physicians are unaware to or unprepared to use digital technologies such as IoMT. As a result, medical physicians must have the knowledge, skills, and mindsets required to fulfil the requirements of today's job needs and to keep up with and benefit from the digital technological advancements in healthcare (European Commission, 2020).

The Theory of DOI lays the groundwork for addressing training as an organisational factor, proposing that training has an impact on technology adoption. Park and Choi (2019) propose that training representing organisational elements can be employed as a determinant of information technology innovation behavioural intention. Consequently, it can be applied to IoMT alongside DOI components. According to a study conducted by Hung et al. in 2016, training is a factor that can help solve challenges associated with the adoption of new technologies. Following this, other researchers found that there is a positive link between relative advantage and training (lim et al., 2020; Huang et al., 2015), however, Raleting and Nel (2011) found that there is no relationship between the two factors. Additionally, the theory of planned behaviour is argued to operate in combination with the theory of DoI to provide the basis to relate relative advantage to training to use IoMT as training is considered to be a behavioural aspect that affects intention (Bronfman et al., 2021; Venkatesh & Bala, 2008). Therefore, if one considers relative advantage as an important factor that describes the diffusion of innovation then its influence on the training of users in IoMT becomes an important consideration as training has implications for continuous usage of IoMT. Knowledge of how training is driven by the relative advantage of IoMT can help users of IoMT to continuously use IoMT. Based on the above, it is possible to posit the following relationship and hypotheses.

The relative advantage of IoMT → Training to use IoMT
H1b: Relative advantage of IoMT positively influences training to use IoMT.

3.3.6. Relationship between compatibility of IoMT and motivation to use IoMT

Organisations find compatibility of IoT devices as an important issue and dissimilarities in devices and problems in interoperability could be issues that can demotivate users (Schoderm 2018). Minoli and Occhiogrosso (2018) argue that if a network allows person to focus on the data required by that person, then that persons is motivated to use IoT. The person should be able retrieve content he or she wants without having the necessity to identify and reach a specific and physical location from where the content has to be retrieved (Datta & Bonnet, 2016; Named Data Networking, 2018; Zhang et al., 2014). These arguments point toward the compatibility of IoT devices to each other and their interoperability which if not found the user may not be motivated to adopt IoT or IoMT.
Compatibility of internet devices, especially those using AI is a major challenge and hence understanding the extent users are motivated to use IoMT become major concern in the literature related to the usage of IoT or IoMT. For instance, Beer and Owens (2018) say that companies like Apple, Google and Amazon are years away from achieving a compatible and shared infrastructure. If one agrees with this argument, then any innovation represented by compatibility as one of the factors of innovation needs to motivate users of IoMT by making the innovation easy to use (Al-Rahimi et al. 2019). Thus, on the one hand, there are compatible problems that concern IoT and IoMT caused

by several factors including AI and on the other IoT and IoMT need to be easy to use and motivate the users to continuously use the technology. Any empirical research that can show the relationship between the compatibility of IoMT to the motivation of users, then the outcome of that research could be useful to organisations and users alike to manoeuvre and control compatibility problems and enhance the motivation of users to accept and use IoMT. As far as theoretical support required to establish a relationship between compatibility and motivation to use IoMT is concerned, both the theory of DoI and SDT are found to provide that support. Furthermore, as explained in section 3.3.4 above that is concerned with the relationship between relative advantage and motivation to use IoMT, compatibility being another diffusion factor similar to that of relative advantage, it is possible to apply the combination of the theories of DoI and self-determination to explain the aforementioned relationship. Thus, the relationship that needs to be investigated and the hypothesis that needs to be tested are:

Compatibility of IoMT → Motivation to use IoMT
H2a: Compatibility of IoMT positively influences motivation to use IoMT

3.3.7. Relationship between the compatibility of IoMT and training to use IoMT

The theory of DOI as an organisational factor explains training to use IoMT (AlSheibani et al. 2020). Many of the technologies whether devices or systems and are developed by different manufacturers IoMT, may not be compatible with the network infrastructure at the end-user's location, making the devices unsuitable to use by the end-users. Thus, there is a necessity to link IoMT compatibility to training to use IoMT arises (Yung-Ming, 2015). Training to use IoMT is explained by the theory of DOI as an organistaional factor (AlSheibani et al. 2020). The need to link compatibility of IoMT to training to use IoMT arises because many of the technologies used by vendors in making IoMT may not be compatible to be connected to the network available at the end users' place which in turn makes the devices incompatible to use by the end users (Yung-Ming, 2015). Particularly, with increasing integration of AI into the healthcare sector and IoMT (Vemuri et al. 2020), organisational readiness to use AI based technologies including IoMT is becoming a challenge. Thus, innovations including IoMT integrated with AI while diffusing and ending in the continuous intention to use the technology, are likely to involve training to use IoMT because of the challenges the users could face in terms of complexity involved in IoMT characterised by AI and the skill needed to use IoMT. The relationship that emerges and the corresponding hypothesis that needs to be tested are:

Compatibility of IoMT → Training to use IoMT

H2b: Compatibility of IoMT positively influences training to use IoMT.

3.3.8. The relationship between the complexity of IoMT and the motivation to use IoMT

Complexity is considered to be one of the critical factors that may negate the motivation to use technology (Huang et al., 2020; Wang et al., 2018). The complex nature of the IoMT, especially with the integration of blockchain and AI, requires committing a significant quantum of resources and time for efficient execution. Consequently, the intense commitment acts as a demotivating factor to use or accept technology (Uddin et al., 2021). Furthermore, certain IoMT solutions require a high cost to be used. Consequently, healthcare practitioners can be discouraged from using them. Complexity has a detrimental impact on motivation to use technology, according to the study (Meltzer et al., 2021; Syed, 2008). Also, Tiago et al. (2016) stated that because innovation is complex, users will find it difficult to use it, and hence will be unable to use or benefit from technology, whereas the empirical study by (Masocha and Chiwenga, 2020) argued that complexity positively influenced motivation, also indicated that if there is an absence or lack of relative advantage, there will be less motivation to accept and deploy innovation. Furthermore, complexity has been found to have a negative loading meaning the higher the complexity, the lower the motivation to adopt a technology or innovation (Zulfitriyana et al., 2020; Ntemana & Olatokun, 2012). Complexity being another diffusion factor similar to that of relative advantage, it is possible to apply the combination of the theories of DoI and self-determination to explain the aforementioned relationship. Applying the above arguments to IoMT, it is possible to conclude that the complexity of IoMT influences the motivation of users' continuous intention to use IoMT. The relationship and hypothesis posited thus are:

Complexity of IoMT → Motivation to use IoMT

H3a: Complexity of IoMT influences negatively motivation to use IoMT

3.3.9. Relationship between the complexity of IoMT and training to use IoMT

Customers prefer to embrace slightly complex innovations, according to Abbas et al. (2017), whereas more complex innovations are difficult to adopt. Furthermore, the literature shows that there is a direct relationship between training and complexity. For example, Tristani et al. (2020) suggested that when the resource is less complicated, more users will be trained in sophisticated technology. Using these arguments and the DOI theory to both the ideas of IoMT complexity and IoMT training, it can be posited that such technology solutions require a high cost to implement and use.

If one applies the arguments of Tristani et al. (2020) it can be seen that the actual complexity of using a resource like IoMT could be reduced if appropriate training is provided. That is to say, if the complexity of technology like IoMT is high, then there could be a corresponding need for the training level to be higher leading to better understanding and use of the technology and its adoption. Furthermore, as explained in section 3.3.5 above that is concerned with the relationship between relative advantage and training to use IoMT, complexity being another diffusion factor similar to that of relative advantage, it is possible to apply the combination of the theories of DoI and TPB to explain the aforementioned relationship. Using these arguments and applying the theory of DOI to both the concepts of the complexity of IoMT and training in IoMT the following can be posited.

Complexity → Training in IoMT

H3b: Complexity of IoMT positively influences training in IoMT

Before proceeding further with the development of the theoretical framework to study the relationship between trialability and observability on the one hand and motivation and training in IoMT on the other, it must be noted here that trialability and observability as determinants of usage of innovations are not common in the literature. For instance, researchers (e.g., Oliveira et al., 2014; Chong et al., 2009; Zhu et al., 2006) highlight that IT adoption trialability and observability are not widely applied in research. In the same vein, some researchers (Al-Rahmi et al., 2019) argue that in motivational studies all the five DOI factors namely relative advantage, complexity, compatibility, trialability and observability. Taking into account these arguments, two decisions were taken. One was that motivation to use IoMT will be driven by the five factors of DOI in line with the study conducted by Al-Rahmi et al. (2019) whereas concerning training in IoMT will be driven only by the three widely used factors of DOI namely relative advantage of IoMT, compatibility of IoMT and complexity of IoMT. Thus, it can be seen that the relationship between the relative advantage of IoMT, compatibility of IoMT and complexity of IoMT on the one hand and motivation to use IoMT and training in IoMT have been already discussed. That leaves only the relationship between observability of IoMT and trialability of IoMT on the one hand and motivation to use IoMT.

3.3.10. Relationship between observability of IoMT and motivation to use IoMT

Observability of innovation is defined as an innovation's outcome which shows that the innovation is noticeable to others (Al-Rahmi et al., 2019; Rogers, 2003). As mentioned in the literature observability and trialability are two innovation factors that are not used widely by researchers in innovation diffusion research because some feel that trialability and observability are not necessarily explained only by the theory of DOI (Martins et al., 2016; Oliveira et al., 2014; Low et al., 2011). This argument brings into focus whether observability will be a useful construct in this research that can explain the continuous use of IoMT and the motivation to use IoMT. To clear this cloud, it is important to understand the concept of observability. The interpretation of the definition of observability of innovation is that if IoMT is useful, then people observe how it is being used, its relative advantage, complexity, compatibility and trialability before intending to use IoMT. Observability appears to be a difficult construct to explain and a concept that could be used to explain the process of innovation and its role in the adoption of IoMT. Although the literature shows that observability is positively correlated to adoption (Sahin, 2006) yet there is no clarity in the literature on whether this indeed is the case across contexts. Furthermore, as explained in section 3.3.4, the relationship between relative advantage and motivation to use IoMT, observability being another diffusion factor similar to that of relative advantage, it is possible to apply the combination of the theories of DoI and self-determination to explain the aforementioned relationship.

In addition, to make the concept parsimonious Parisot (1997) has argued that role model is the key factor that will enable users to be motivated and adopt IoMT. However, taking the recommendations of Al-Rahmi et al. (2019) who says that there is a need to examine the exact role and influence of observability on motivational factors and noting that no research has been conducted to ascertain the relationship between observability of IoMT and motivation to use IoMT, this research posits:

Observability of IoMT → Motivation to use IoMT
H4: Observability of IoMT positively influence Motivation of IoMT

3.3.11. Relationship between trialability of IoMT and motivation to use IoMT

There is evidence in the literature that shows that trialability as a diffusion factor affects the motivation of users of the innovation (e.g., Al-Rahmi et al., 2019). The definition of trialability says trialability is the ease with which an innovation can be experimented with (Rogers, 2003). If one uses this definition, it can be seen that the trialability of IoMT needs to be tested for the ease with which it can be used. It must be mentioned here that calls could be found in the literature for testing the linkage between trialability and motivation concerning online technologies for instance Al-Rahmi et al. (2019) called for examining this relationship in the context of e-learning. It must be understood here that DOI is more useful to be applied to the individuals rather than organisations (Senarathna, 2018; Rogers, 1995) and hence it is significant to this research. In addition, as explained earlier in this section, where it is shown that the relationship between relative advantage and motivation to use IoMT is explained using the theories of DoI and self-determination, it is possible to argue that trialability being another diffusion factor similar to that of relative advantage, it is possible to apply the same two theories in combination to explain the aforementioned relationship. Thus, the relationship that emerges and the hypothesis that could be formulated are:

Trialability of IoMT → Motivation to use IoMT
H5: Trialability of IoMT positively influences motivation to use IoMT

3.3.12. Relationship between intrinsic motivation and continuous intention to use IoMT

From the literature review (see section 2.15), it can be seen that motivation is an aspect that determines continuous intention to use an innovation. From figure 2.8 it can be seen that motivation as a concept is driven by the perception of the features of the actual innovation, which is determined by the five DOI factors. Conceptualising the five factors of DOI as determinants of motivation (intrinsic or extrinsic) to use IoMT is rarely found in the literature. The publications of Al-Rahmi et al. (2019) and Baudier et al. (2019) have brought out the importance of motivation as a mediating construct between diffusion of innovation and continuous intention to use innovation. In the case of Al-Rahmi et al. (2019), it is argued that the TAM constructs perceived usefulness and ease of use as well as the intention to use are representing the concept of motivation. However, in the case of Baudier et al. (2019) it is seen that motivation as a construct has been used alongside TAM constructs indicating a clear contrast between the approaches adopted by Al-Rahmi et al. (2019) and Baudier et al. (2019). This contradiction could arise from the conceptualization of motivation. Literature shows that perceived ease of use, perceived usefulness and continuous intention to use technology, are representing motivation. Literature also shows that the concept of motivation can also be represented by various other components including self-determination. For instance, if technology like IoMT is perceived to be useful and easy to use, then most often users will intend to use IoMT. This is well established by TAM.

However, if the users' self-determination comes into the picture and users find that as an innovation not much is known about IoMT, then unless users have the motivation to use new things in their life, self-determination will not help them take the first steps of trying to use IoMT. On the contrary, if the user is having a motivation to try new things in life, then self-determination will certainly act as a driver to push the user to adopt IoMT. This needs to be tested as there is no compelling evidence in the literature that shows motivation to use IoMT is an automatic phenomenon that will happen automatically. Here self-determination theory becomes handy alongside the theory of DoI and the combination of the two theories could be used to support the establishment of the relationship between motivation to use IoMT and continuous intention to use IoMT. Thus, IoMT as innovation needs to motivate the user to use IoMT. An actual example of motivation could be the feeling of autonomy while using technology (Baudier et al., 2019), for instance, IoMT. From the above arguments, it can be seen that the following relationship and hypothesis could be posited.

Motivation of IoMT → Continuous intention to use IoMT

H6: Motivation to use IoMT positively influences continuous intention to use IoMT

3.3.13. Relationship between training to use IoMT and continuous intention to use IoMT

From the literature review (see section 2.16) it can be seen that training is an aspect that determines continuous intention to use an innovation. It can be seen from the literature review in section 2.16.1., that training as a concept is driven by the perception of the features of the actual innovation and which can be determined by the 5 DOI factors. Conceptualising the five factors of DOI as determinants of training to use IoMT is hardly found in the literature. Literature shows there is a lack of knowledge on how training in IoMT as a concept has to be understood concerning the use of technologies and new technologies (e.g., Gaynor et al., 2015; Al-Gahtani, 2016) especially so about a diffusing technology. Further, where the motivation of individuals is involved in research, then training becomes an automatic choice, as training is considered to be an associate construct of motivation (see section 2.6.6).

The concept of training is a complex one. Training involves several components including the trainer, the trainee, the skill, the resources, the training infrastructure, learning outcomes and certification. Literature shows that using and maintaining IoT invariably requires training (Boyarchuk et al., 2019; Nagy et al., 2018; Fathema et al., 2015) an argument applicable to IoMT also. Further, sometimes training may have to be initiated at the initial phase of diffusion itself. Thus, training assumes significance in this research. Additionally, to what extent training in IoT can determine the continuous intention to use IoMT is not understood well. Whether all training as a construct and concept needs to be investigated is an important point to ponder. From the literature review given in section 3.3.13, it can be seen that lack of training, or improper training, can play a negative role in the process of diffusion as well as usage of any technology including IoMT. Lack of training has the potential to build a negative perception about IoMT and hence its consequent usage.

As far as the theoretical support to establish the relationship between training and continuous intention to use IoMT is concerned, based on the arguments given in section 3.3.13, it is possible to argue that training can be explained using TPB. The continuous intention to use IoMT could be explained using the theory of DoI. Thus, the combination of the two theories can be used to establish the relationship between the two constructs. Therefore, it is reasonable to infer that training can affect behavioural intention to use IoMT of IoMT. From the above it can be seen that:

Training in IoMT → Continuous intention to use IoMT

H7: Training in IoMT positively influences continuous intention to use IoMT

3.4. Relationship between moderators and DOI factors

While the foregoing discussions have shown the way DOI factors can be linked to motivation to use IoMT, training in IoMT and continuous intention to use IoMT, this research also posits that researchers have argued for a need to include moderating variables of the main theoretical relationships described above. This section deals with this aspect. Moderators are variables that enable an understanding of whether the relationship between a dependent and independent variable is likely to be influenced by a third variable seen in terms of the nature (e.g., magnitude and/or direction) of the dependent variable (Aguinis et al., 2017) for instance age and gender are considered moderators in UTAUT. Normally moderators are used to verifying "when" or "for whom" a variable strongly explains or causes an outcome variable (Frazier et al., 2004). As for as diffusion of innovation variables is concerned, seldom does come across the moderating variables that moderate between the five innovation variables (e.g., relative advantage, complexity, compatibility, observability and trialability) and the dependent variable (e.g. intention to use the innovation). However, it is always possible that some moderator always works on the relationship effect which usually goes unnoticed. For example, in the current research the variables relative advantage of IoMT, the complexity of IoMT and compatibility IoMT are linked to training in IoMT. Training in IoMT usually could involve additional factors other than those concerning IoMT, for instance, awareness of the users about the latest technological tools (e.g., artificial intelligence) may affect the user capability of IoMT of the users in both the direction and magnitude. In such cases just verifying the linkage between the independent and dependent variables alone will yield a complete picture of the variation of the dependent variable. The same arguments apply to the relationship between the antecedents of continuous usage of IoMT and continuous usage of IoMT. For instance, usage intention as a dependent variable is affected by moderators' age, gender and experience in its relationship with its antecedent e.g., hedonic motivation in UTAUT (Venkatesh et al., 2012). Taking into account real-life situations, it is worthwhile to examine the interaction of moderators in the relationship between the independent and dependent variables. Thus, research examines in a limited way how the following moderators' function with regard to specific independent-dependent variable relationships.

3.4.1. Moderation of the relationship between antecedents of continuous intention to use IoMT and continuous intention to use IoMT

Venkatesh et al. (2012) argue that moderators play a role in the relationship between intention to use technology and its antecedents. While developing the UTAUT, Venkatesh et al. argued that the relationship between independent variables like hedonic motivation and use behaviour is moderated by variables like age, gender and experience. UTAUT as a model has been tested by many researchers for its validity, for instance, Venkatesh et al. (2016) (also see Merhi et al., 2019; Khechine & Lakhal, 2018; Abubakar & Ahmad, 2013). Venkatesh et al. (2012) in their seminal work posit that age will moderate the effect of hedonic motivation on continuous intention. That age moderates the relationship between hedonic motivation and use behaviour posited by UTAUT is verified by many in the literature (e.g., Merhi et al., 2019; Viot et al., 2017; Tarhini et al., 2015). These arguments lead to the conclusion that antecedents of user behaviour and their relationship to determinants of use behaviour like hedonic motivation are moderated by age as a construct and such a relationship are supported by UTAUT. Similar arguments could be extended to the moderation of the relationship between training to use IoMT and continuous intention to use IoMT as training is considered to be a close associate of motivation.

3.4.2. Age as a moderator of the relationship between motivation to use IoMT and continuous intention to use IoMT

The foregoing arguments point out that age can act as a moderator of relationships in a model that concerns to use a technology a statement that is supported by UTAUT (Venkatesh et al., 2012). This includes the current research model where the motivation to use acts as one of the antecedents of continuous use of IoMT and its relationship with continuous intention to use IoMT could be hypothesised to be moderated by age of the users. This implies that people in different age groups will be motivated variedly to continuously use IoMT. As early as the late nineties of the previous century Chau and Hui (1998) argued that when an innovation is in its beginning stages of diffusion, younger people are likely to exhibit a greater tendency to seek innovativeness when compared to older people. This is visible even now where it is possible to see that younger people seek to use the latest mobile phones like the iphone in comparison to older people. In addition, younger people are motivated more than the elderly to make decisions concerning technological innovation. However, whether is this the case with IoMT is an important concern of researchers as IoMT is widely used by old people under examination and age-dependent data has to be collected periodically to build a data bank of values that could be used in treatment (Baker et al., 2017). In this case, continuous use of IoMT is inevitable and age moderates the motivation to continuously use IoMT by older people. Yet when innovation is diffusing, it is not clear whether young and old people behave differently regarding continuous intention to use the innovation because Pew (2018) showed that young people falling within some income and education groups were more interested in a smartphone for communication than online access while Pew (2014) argued the 90% of adults were using cell phones although only 64% amongst them had smartphones. These arguments could also be applied to IoMT and the use of IoMT by young and old people. This shows that the use behaviour of young and old people is unpredictable and needs to be examined in every context. In addition, the moderation effect of age can be explained by the UTAUT model the justification, which has been explained in section

2.17.1 Thus, the moderation effect of age on the relationship between motivation to use IoMT and continuous intention to use IoMT can be depicted as given under (see figure 3.1).

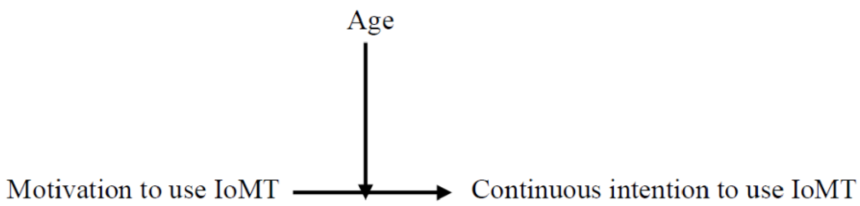


Figure 3.1: Moderation of Motivation to continuous intention to use IoMT by AI Age

While it is not clear whether increasing age or decreasing age moderates the motivation of people to continuously use IoMT, it is assumed that the older the age, the more continuous will be the intention to use IoMT whereas younger the ageless continuous will be the intention to use IoMT. The reason could be that older people may find it difficult to cope with the fast-paced changes in technology when compared to young people who would be interested to adopt the latest innovation faster than older adults. Thus, the hypothesis that is posited as follows (see figure 3.2).

H8: Age moderates the relationship between motivation to use IoMT and continuous intention to use IoMT positively in older adults and negatively in younger people.

3.4.3. Age is a moderator of the relationship between training to use IoMT and continuous intention to use IoMT

As in the case of motivation to use IoMT and taking into consideration that motivation and training are interrelated (Ozkeser, 2019), it can be anticipated that younger person could be trained faster when compared to older people and hence the usage of innovations could be achieved faster in the case of younger people than in the case of older adults. Literature shows that motivation increases with a higher level of training in technology (e.g., Khan et al., 2020; Mustapha, 2020). For instance, the survey conducted by AARP Research, (2019) shows that concerning wearables younger adults in the age group of 18-49% and old people above 50 adopt and use similarly. This implies that training could have helped everyone to be motivated equally in using wearables regardless of age. On the other hand, younger generations have abandoned tablets in comparison to older generations that are still using tablets. This may be because younger ones can learn faster and are motivated to a higher level when compared to older ones which imply the impact of training on the younger generation is higher than the older generation. Considering the arguments given in the previous section where it is seen that older people may require more motivation to use innovations like IoMT, when compared to younger adults, it can be posited as follows (see figure 3.2).

Age as a factor moderates the relationship between training to use IoMT and continuous intention to use IoMT. As explained earlier (see section 2.17.1) UTAUT is used as the theory to explain the moderation by age of the relevant relationships mentioned above.

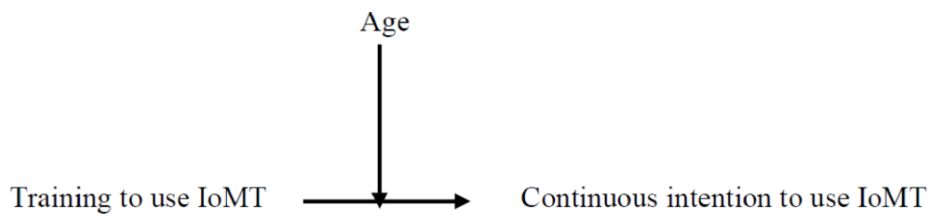


Figure 3.2: Moderation of Training to Continuous intention to use IoMT by Age

The hypothesis that can be posited is:

H9: Age moderates the relationship between motivation to use IoMT and continuous intention to use IoMT positively in older adults and negatively in younger people.

3.4.4. Novelty seeking as a moderator of the relationship between motivation to use IoMT and continuous intention to use IoMT

Literature (e.g., Venkatesh et al., 2012) posits that novelty-seeking behaviour is an important reason for the influence of users' motivation to use innovations. Novelty seeking behaviour has been of interest to researchers for the last few decades (e.g., Dabholkar & Bagozzi, 2002; Chau & Hui, 1998; Hirschman, 1980; Midgley and Dowling, 1978). Novelty seeking denotes the tendency of a person to seek out novel information or stimuli (Venkatesh et al. 2012; Hirschman,1980). However, while discussing the topic novelty-seeking by users of technology literature shows that some important concepts have been related to it including innovativeness, motivation, training, adoption of technology and decision to use technology (Venkatesh et al., 2012). However, conceptualisation of novelty seeking has been varying for instance Tsao and Yang (2017) have used novelty seeking as a determinant of intention to use while others (e.g., Andreassen & Streukens, 2013) have used it as a moderator of the relationship between attitude and intention to use or perceived usefulness and attitude (e.g., Babić-Hodovićj & Arslanagić-Kalajdžić, 2019). More articles appear to have conceptualised novelty seeking as a moderator of relationships where the determined variable is the intention to use or attitude (e.g., Um et al., 2020; Dabholkar & Bagozzi, 2002). As far as the theoretical support for conceptualizing novelty-seeking behaviour as a moderator, this research relies upon the UTAUT model. Justification for using UTAUT as the theoretical base is explained in section 3.4. Thus, keeping in view the wider recognition of conceptualising novelty seeking as a moderator in the literature this research uses novelty seeking as a moderator.

3.4.5. Novelty seeking as a moderator of the relationship between motivation to use IoMT, training to use IoMT and Continuous Intention to use IoMT

It is argued in the literature (Venkatesh et al., 2012) that novelty-seeking behaviour affects the motivation of a person that drives the continuous intention to use the technology of users of innovation. For instance, Um et al. (2020) while studying the attitude and intention of users in the context of comparing the influence of intelligence chatbots and self-service technology for sustainable services posited that novelty-seeking moderates the relationship between service success and attitude which is linked to intentions. Similarly, Dabholkar and Bagozzi (2002) argued that inherent novelty seeking moderates the relationship between ease of use (a motivation factor) and attitude which was linked to intention to use. While these two examples show that the relationship between motivation and intention to use or continuous intention to use can be moderated by novelty-seeking there is no clarity in the literature on whether IoMT usage can be considered a novelty in the field of healthcare and the relationship motivation to use IoMT and continuous intention to use IoMT will be moderated by novelty seeking. No paper has specifically addressed this concern due to which it is not known whether novelty seeking as a moderator has any benefit at all. The same argument goes for training to use IoMT because training in IoMT is linked to motivation to use IoMT and the relationship between training to use IoMT and continuous intention to use IoMT will be moderated by novelty seeking. In both cases, there is no clear knowledge in the literature on how the moderating effects of novelty-seeking could shape the continuous intention to use IoMT. Conceptualising novelty-seeking behaviour as a moderator was based on UTAUT justification, which is provided in section 3.4.4. Taking into account the fact that the results of employing novelty seeking as a moderator by researchers including Um et al., (2020) and Dabholkar and Bagozzi (2002) this research investigates the following relationships to examine the impact of novelty seeking on the two relationships namely (see figure 3.3).

- Relationship between motivation to use IoMT and continuous intention to use IoMT
- Relationship between training to use IoMT and continuous intention to use IoMT

Thus, it can be posited that

The hypotheses that are postulated are:

H10: Novelty seeking positively moderates the relationship between motivation to use IoMT and continuous intention to use IoMT.

H11: Novelty seeking positively moderates the relationship between training to use IoMT and continuous intention to use IoMT.

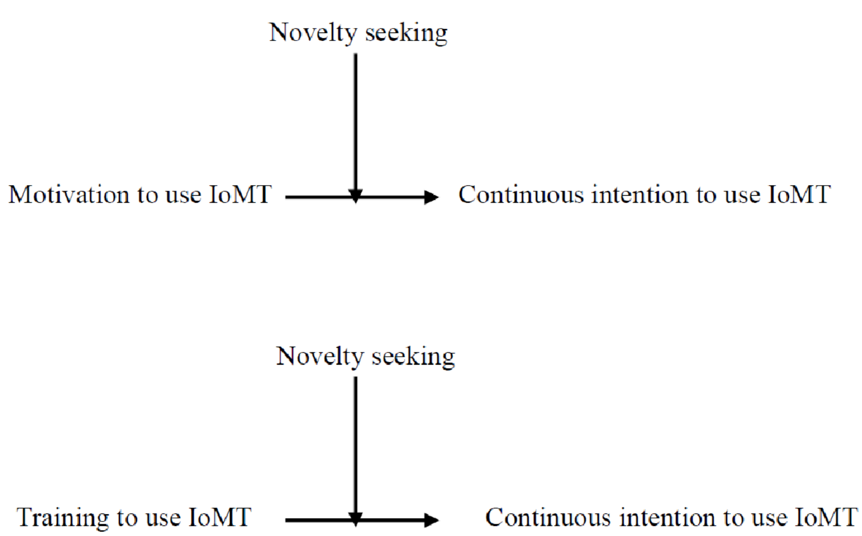


Figure 3.3: Moderation of Motivation to Continuous intention to use IoMT by Novelty Seeking and Moderation of Training to Continuous intention to use IoMT by Novelty Seeking.

3.4.6. Moderation of the relationship between the relative advantage of IoMT and training in IoMT by awareness of artificial intelligence

Literature shows that AI is one of the main enabling technologies (Chen, 2019). AI is playing a major role in the healthcare sector (Arab Health, 2019). AI is turning out to be an important innovation that is promising to change the way people view things with AI currently flourishing in many industries including healthcare (Chen, 2019; CAICT and Gartner, 2018). However, awareness about AI as innovation is still percolating amongst the people and concerns have been raised about its trustworthiness for use in applications (Ashoori & Weisz, 2019). According to Rogers (2003) awareness of innovation is the first step in innovation and extends up to its continued use. While IoMT is still diffusing, another powerful technology namely AI is already influencing IoMT (Arab Health, 2019). Together with AI, how the diffusion of IoMT will shape is not clear. In this situation, the direct relationship between the relative advantage of IoMT and training in IoMT could be seriously affected by AI.

To test this effect of AI, in this research, a new moderating construct namely awareness about AI has been introduced. Support for this conceptualization is provided by Almansoori et al. (2021) who provide the evidence to conceptualise artificial intelligence awareness as a moderator. The influence of AI awareness on training to use IoMT could be explained by TPB. Thus, a combination of the theories of DoI and planned behaviour is used to conceptualise AI awareness as the moderator of the relationship between relative advantage and training to use IoMT. Thus, the following relationship was identified for this research (see figure 3.4).

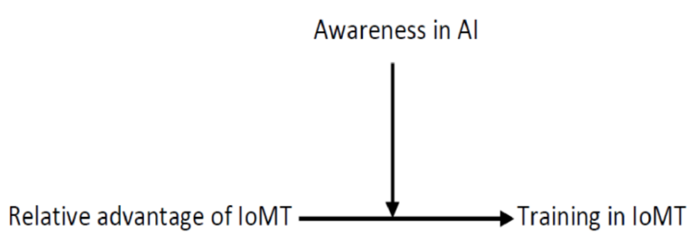


Figure 3.4: Moderation of Relative Advantage to Training by AI Awareness

The hypothesis that is posited is given below

H12: Awareness about AI negatively moderates the relationship between the relative advantage of IoMT and training in IoMT

3.4.7. Moderation of the relationship between the complexity of IoMT and training in IoMT by awareness in Artificial Intelligence

IoMT is turning out to be a major influencing technology on human beings and the healthcare sector. However, complexities are causing concern and could drive away users from employing IoMTs. One way to overcome complexities will be to train users. Literature shows that (e.g., Taylor et al. 2018) users of IoMT including healthcare organisations, service providers and patients lack understanding about the added value the interconnected medical devices provide and how to use them at scale and thus derive improved economics and patient care. One way to improve this understanding was by training the users of IoMT and supporting them to embed the required skills that can enable them to optimise the use of IoMT and make it easy to use (Taylor et al., 2018). However, despite providing training and support to the users, it is not clear whether training as a factor is perceived by users as important or is another challenge in itself.

To make the training aspect meaningful and easy to understand for users, awareness about AI needs to be introduced, which will make IoMT an innovation which is completely diffused the more it is used. Thus, if awareness about AI as a moderator is introduced in the relationship between the complexity of IoMT and training to use it, then the user's training in IoMT could be easier than before and more useful. As far as the theoretical support to conceptualise AI awareness as a moderator is concerned, the same arguments given in the previous section can be used. These are the application of the theories of DoI and planned behaviour to the relationship between compatibility and training to use IoMT. Applying these can help the understanding of the moderation of the relationship between complexity and training to use IoMT by AI awareness, as complexity is seen to be another diffusion dimension like compatibility. Based on this argument the following conceptualisation is posited (see figure 3.5).

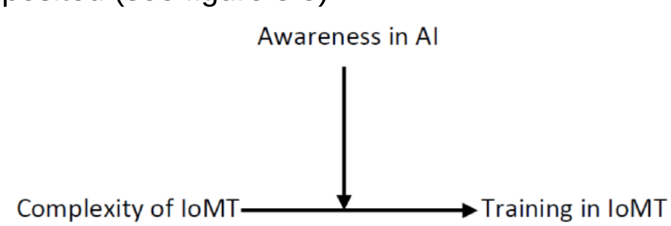


Figure 3.5: Moderation of Complexity to Training by AI Awareness

The hypothesis that can be postulated is

H13: Awareness in AI negatively moderates the relationship between complexity in IoMT and training in IoMT.

According to the literature, complexity has a direct relationship with training in IoMT (Tristani et al., 2020) argued that the training in IoMT required will be more useful the less complex IoMT integrated with AI is). To reduce this, awareness about AI in IoMT could be used as a moderator. A complete search through Google did not yield any result which could show that this aspect has been empirically tested already.

3.4.8. Moderation of the relationship between the compatibility of IoMT and training in IoMT by awareness in artificial intelligence

Literature shows that compatibility of technology is an issue in adoption behaviour (Chen, 2019; Oliveira et al. 2014; Azadegan & Teich, 2010; Dedrick, & West, 2004; Chong & Bauer, 2000). For instance, Fornasier (2019) argues that the biocompatibility of sensors could be a technological issue that needs to be sorted out while implementing IoMT. Compatibility is a major concern that affects the adoption rate of IoMT (Qureshi & Krishnan, 2018). Qureshi and Krishnan (2018) argue that decision-making systems like IoMT integrated with AI are a major challenge for users of IoMT and that IoMT requires extensive changes to their existing technologies which could affect the adoption rate of IoMT. Furthermore, Holmes et al. (2019) argue that handling IoMT will require technicians and users to have new capabilities and hence training is needed. This is more amplified at present with the advances made in artificial intelligence that have brought out such new concepts as machine learning, virtual learning and deep learning that are promising to revolutionise the application of AI to different technologies including IoMT (Nguyen et al., 2021).

It is shown in previous sections that the compatibility in IoMT positively influences training in IoMT (see section 3.3.7). If a moderator is introduced in this relationship, then perhaps the innovation will add value and provide a greater experience to the users (Rogers, 1995). In the previous section, it was argued that there is evidence in the literature which show that Almansoori et al. (2021) have conceptualised as moderators in their research on organisational performance. Thus, it can be argued that introducing awareness of AI as a moderator in the relationship between compatibility in IoMT and training in IoMT could enable users to gain through the training leading to faster adoption of IoMT and hence its continued use. As far as the theoretical support to conceptualise AI awareness as a moderator is concerned, the same arguments given in the previous section could be applied. These have to do with the application of the theories of DoI and planned behaviour to the relationship between relative advantage and training to use IoMT. By applying these arguments, it is then possible to understand the moderation of the relationship between compatibility and training to use IoMT by AI awareness, as compatibility is another diffusion dimension like relative advantage. Taking the above arguments into consideration the following conceptualisation can be posited. (See figure 3.6)

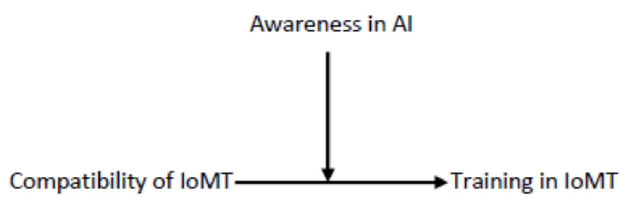


Figure 3.6: Moderation of Compatibility to Training by AI Awareness

The hypothesis that can be posited is:

H14: Awareness in AI negatively moderates the relationship between compatibility in IoMT and training in IoMT.

The final theoretical model that emerges from the above discussions is given in figure 3.7

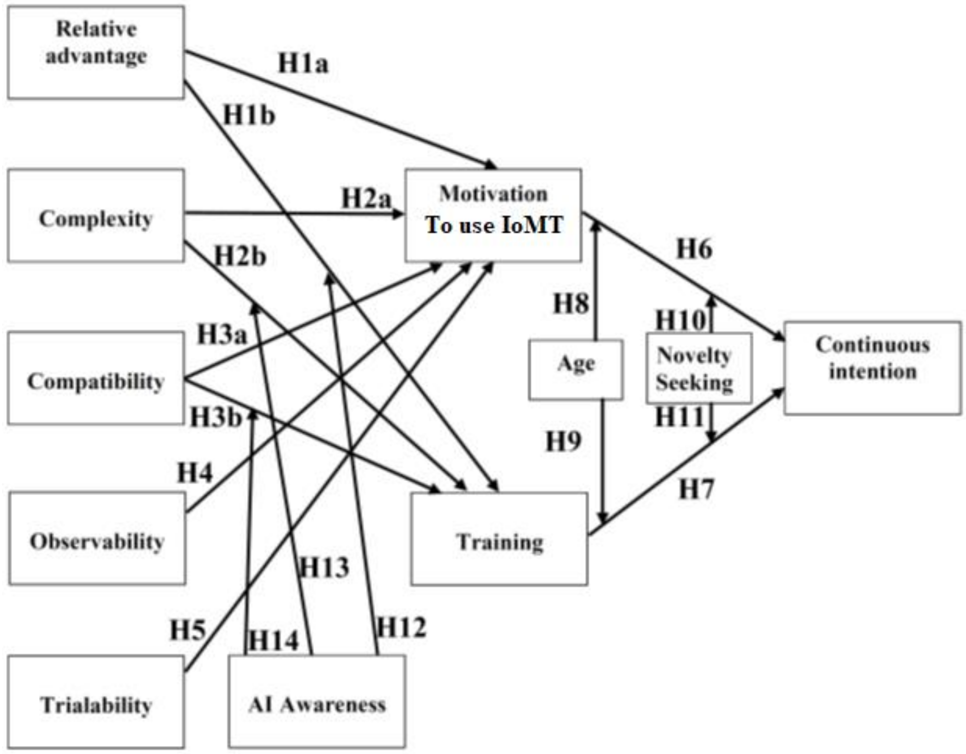


Figure 3.7: Theoretical framework linking DOI factors, motivation, training and continuous intention to use IoMT

3.5. Conclusion

This chapter provides the models that have emerged from the theoretical framework set for this research. The theoretical model shown in figure 3.7 provides the basis to directly test the impact of DOI factors on the continuous intention of users to use IoMT with motivation and training to use IoMT as intervening variables. Furthermore, the chapter has discussed the importance of the moderators that impact the paths drawn in depicting the relationship between the DOI factors and continuous intention to use. Thus, this chapter has laid down the basis for the research methodology that has been developed to test the model.

4. Chapter 4: Research Methodology

4.1. Introduction

This research investigates the core issue of the continuous intention of healthcare professionals (clinicians and nurses) to use AI-based internet of medical things (IoMT) during its diffusion. The research questions aim to understand to what are the factors that could influence and affect the continuous intention to use AI-based IoMT and the extent to which those factors could influence and affect the continuous intention to use AI-based IoMT. To understand the extent to which those factors could influence and affect the intention to use AI-based IoMT of healthcare professionals, a conceptual model was developed (see figure 3.7) and hypothetical relationships were formulated. To test and validated those relationships, in this chapter the research methodology used has been defined. Thus, subsequent sections describe the choice of the methodology used in this research and the justifications thereof. The methodology involves determining the choice of the epistemological and ontological stance adopted by the researcher, the reach approach employed and the research methods to be used. Furthermore, the sections dwell on the research framework that has been employed, the development of the reached design that was used in the research, the research strategy that was adopted, the sampling methods used, the data collection strategy implemented, and the data analysis used. Each of these aspects has been described next.

4.2. Epistemological considerations

The word epistemology is a combination of two words episteme and logos which are originating from the Greek language where the word “episteme” is referred to as knowledge or understanding and the word “logos” is referred to as reason or argument (Altay, 2021; Perla and Parry, 2011; Buehl & Alexander, 2001). The term is used in research to describe how it is possible for researchers to come to know about something, such as the truth or reality (Kivunja & Kuyini, 2017). According to literature (Crotty, 1998;

Petty et al., 2012), epistemology is described by how researchers are obtaining and gaining knowledge and facts.

Saunders et al. (2019) argue that epistemology is a concept that deals with acceptable knowledge and what constitutes acceptable knowledge in the relevant field of research. Widely used epistemological positions by researchers include positivism and interpretivism (Sekaran & Bougie, 2019; Saunders et al., 2019). For instance, in the field of IoMT the knowledge concerning the determination of continuous intention to use IoMT is not well understood. For instance, Tsourela and Nerantzaki (2020) argue that past studies while investigating and enriching current knowledge about factors influencing consumers' intention to use information systems, but those factors appear to have not been comprehensively investigated. This shows that current knowledge about IoMT and continuous intention to use IoMT is incomplete and requires the adoption of an appropriate epistemology to understand IoMT and continuous intention to use IoMT.

Furthermore, as can be seen from the literature, epistemology is related to the researchers' views of what is to be considered important in a study (Saunders et al., 2019). In addition, epistemology concerned either the collection and analysis of facts or observations (Kivunja & Kuyini, 2017) that could be understood based on the feelings and attitude of the researcher that may be viewed as having no external reality (Deonna & Teroni, 2021). For instance, the continuous intention of healthcare professionals to use IoMT could be understood as real or not by collecting data about the continuous intention to use behaviour of those healthcare professionals understudy or by observation and remaining in enclose proximity of those professionals to determine their intentions. In both cases, the knowledge about the continuous intention of healthcare professionals to use IoMT could be extracted by analysing the data. However, according to literature (Jungmann, 2021; Ryan, 2018) it is the belief of the researchers concerned that will direct the epistemological stand to be adopted by the researcher. Broadly these beliefs of the researcher's concern could be brought under two philosophies or paradigms namely positivism and interpretivism (Saunders et al., 2019). These are discussed next.

4.2.1. Positivism

The term positivism was founded by the distinguished and well-known French philosopher and father of sociology Comte (1798–1857). Comte (1830) argued that society will be analysed using positivism as an approach and predicted that all actual knowledge would come from human observation of objective reality and underlined that the object of research is based on empirical evidence (Noordin & Masrek, 2016; Bourdeau, 2010). According to (Creswell & Creswell, 2018) positivism is about what is observable by human senses that is factual. This means that there is an existence of objective universal reality, and such reality is governed by universal laws and mechanisms (Creswell & Creswell, 2018). The researcher who follows this tradition holds the role of an objective analyst, who interprets data by separating facts and their value as stated in Saunders et al. (2019) and Robson (2002). Positivism is also called the standard view in science, which simply searches for the existence of constant interaction between events, or between two factors, in the language of experiments (Robson, 2002).

Further positivism is expected to lead a researcher to collect credible data that will be used to verify and confirm certain hypotheses (Ryan, 2018). Verification of the hypothesis is likely to lead to the expansion, extension or confirmation of the existing theories (Saunders, et al., 2019). Another important aspect of positivism is the search conducted in a value-free manner (Steel et al., 2018). This implies that the resources used by the researcher are external to the data collection process. This entails that the researcher is independent of the subject of the research because of which the researcher neither affects nor is affected by the subject of the research (Remenyi et al., 1998).

Furthermore, Žukauskas et al. (2018a) confirmed that positivism and objectivism are closely tied and linked with facts, statistics, measurements, and numbers, rather than the opinions and values of researchers (Bryman & Bell, 2007; Weber, 2004). Further, Pervan (1994) indicated that positivism posits that the phenomena under investigation are real and can be measured by external or outside observers. The researchers would explain their opinions to examine the social world using this philosophical method and they refer to objectivity rather than subjectivity (Cooper et al., 2006). The positivism paradigm aids positivist scholars in clearly comprehending the objects using empirical tests and methods such as sampling, measurement, questionnaires, and focus group discussions (Pham, 2018), besides, it has evolved into a strong sociological tool (Majeed, 2019). Experimental and quasi-experimental approaches are employed by positivist research based on ontological and epistemological theories (Creswell, 2007). In addition, it can be seen that according to the literature positivism is linked usually to objective ontology, adaptive approach and quantitative methods (Park et al., 2019).

The strengths of positivism include:

- Grounded in research methods that are considered a scientific method of investigation (Kaliyamurthi, 2021).
- Generation of generalisable and replicable findings (Polit et al., 2013; Denzin & Lincoln, 2011).
- Enable research of the cause-and-effect relationship in nature (Addae & Quan-Baffour, 2015).
- Try to interpret observation based on facts or measurable quantities (Kelly et al. 2018).
- researchers could save time and money by relying on the findings of a single study to make quantitative estimates in the future (Johnson & Onwuegbuzie, 2004).

The limitation of positivism include:

- Phenomenon and study cannot be those that could be understood using senses of sight or smell or touch, taste and hearing (Sousa, 2010).
- Assumption for social scientists that social reality can be explained using rationality as it is assumed that people act rationally, however real life is not always about rational behaviour as individuals may act subjectively without acting rationally (Sousa, 2010).

  Research is limited to phenomena that can be observed and measured objectively whereas in reality, many phenomena may not be observable or objectively measurable (Chirkov & Anderson, 2018).

As far as the current research is concerned if the researcher adopts positivism, then it implies that continuous intention to use IoMT is observable and reality that could be measured objectively. In addition, it also implies that the phenomenon of continuous intention to use IoMT can be explained by conducting scientific research through the collection of data. It also could lead to a result that can be explained using scientific laws thereby confirming or falsifying assumptions or hypotheses used to investigate the phenomenon of continuous intention to use IoMT. The above discussion clearly points out the various criteria that need to be considered if a researcher wants to adopt a positivist epistemology. After discussing positivism, the net section discusses interpretivism.

4.2.2. Interpretivism

The interpretive framework is a theoretical approach that entails a systematic examination of socially relevant behaviour in order to gain a better explanation of how people construct and sustain their social worlds (Kelly et al., 2018; Neuman, 1997) where there is no single truth under the interpretive paradigm (Nguyen, 2019; Bucci, 2002). According to Hammersley (2013, p. 26) interpretive paradigm is founded on the idea that methods used to comprehend knowledge in human and social sciences cannot be the same as those used in physical sciences because humans interpret their environment and then act on it, but the world does not. Robson (2011) indicated that the main purpose of interpretivism research is to capture and comprehend multiple perspectives on an event that has been "lived, felt, and undergone". Interpretivism adopt a relativist ontology, in which a single phenomenon can have various interpretations rather than a single fact that can be determined through a measurement procedure (Pham, 2018). According to Takahashi and Araujo (2020), positivists consider social phenomena as a world of causal relationships in which a single truth can be discovered and proved while interpretivism believes in the opposite (Kivunja & Kuyini, 2017). Greene (1992) highlighted the difference between positivism and interpretivism and said that information is strongly attached within the subjective ontology which is concerning the interpretive paradigm. The most beneficial aspect of interpretive epistemology is that the interpretive researchers may not only describe objects, people, or events but also profoundly grasp them in their social contexts, due to their diverse perspectives of phenomena (Pham, 2018).

The major drawbacks of interpretivism are that it has a subjective rather than objective ontological perspective as well as it totally ignores and neglects the questions of power and agency that are present in modern society (Mack, 2010). Surprisingly, this limitation may have prompted critical inquiry to play a larger role in improving the feasibility of the research. As a result, research findings are unquestionably influenced by the researcher's interpretation, belief system, methods of thinking, or cultural preferences, resulting in a variety of biases. Another weakness is that it ignores the ideological and political influences on information and human reality (Pham, 2018; Mack, 2010). It must be noted here that interpretivism is linked to subjective ontology, inductive research approach and qualitative research methodology (Creswell & Creswell, 2018; Saunders et al., 2019; Holden & Lynch, 2010). Furthermore, while literature shows that positivist research philosophy is the most widely used in empirical research concerning management and business topics including topics concerning continuous intention to use IoMT, the use of interpretive research philosophy in IoMT use research is gaining momentum (Saarikko et al., 2020; Folkerts et al., 2020). Based on the discussions given above it can be seen that the adoption of interpretive research philosophy in any research needs to understand both the strengths and limitations of the philosophy before it is considered for use in empirical research.

4.3. Ontology

Ontology refers to the nature of knowledge and reality (Creswell & Creswell, 2018; Lincoln, et al., 2011) and is usually concerned with the subjective and objective nature of reality. The subjective ontology refers to social phenomena as being created from the perception and consequent actions of the social actors (Saunders, et al., 2019). For example, social actors could be healthcare professionals and their perceptions and actions with regard to IoMT could lead to applying the concept of IoMT through the process of social interaction with patients leading to the social phenomena being in a constant state of revision. Usually, subjective ontology is associated with interpretivism philosophy (Al-Ababneh, 2020) that necessitates exploration of the subjective meanings of phenomena that motivate the action of social actors enabling researchers to interpret and understand those actions (Saunders et al., 2019; Crotty, 1998). The subjective ontology is also associated with interpretive research philosophy, inductive research approach and qualitative research methods (Creswell & Creswell, 2018; Saunders et al., 2019; Holden & Lynch, 2010).

On the other side of the subjective ontology is the objective ontology usually considered in the opposite side of the subjective ontology continuum (Holden & Lynch, 2004).

Objective ontology assumes that social entities exist in reality, and such entities are external social actors (Saunders, et al., 2019). For example, in the case of healthcare professionals who are using IoMT in their jobs could use IoMT for supporting the patients and managing healthcare in a way that management is independent of any single professional. This implies that healthcare management remains the same for many professionals who are attending to the patients indicating that healthcare management using IoMT is a phenomenon that is independent of the healthcare professionals who are the social actors. Objective ontology is usually related to positivist research philosophy, deductive research approach and quantitative research methods (Holden & Lynch, 2004). Limitations of adopting subjective ontology include the assumption that reality is a subjective phenomenon and outcomes are affected by the bias of the researcher who investigates the phenomenon (Pham, 2018). Limitation of objective ontology includes those objective aspects of phenomena are considered more important compared to subjective knowledge whereas in reality, some managers may consider subjective decision making to be more important (Pham, 2018). In this situation objective ontology fails to explain the subjective behaviour of social actors thus it's important for researchers to understand the actual nature of the phenomenon, they are investigating before choosing the ontological stand. After understanding the concept in ontological stands the researcher can assume the next section discusses the research approach that needs to be adopted by researchers.

4.4. Research approach

Usually adopted research approaches include the deductive approach and inductive approach (Bonner et al., 2021). While the deductive approach helps in deducing results by deducing hypotheses from a theory, the inductive approach believes in building a theory (Creswell & Creswell, 2018). Both inductive and deductive approaches are considered to be opposite to each other (Holden & Lynch, 2004).

The deductive approach aims to answer the research questions by proposing the relationships between two variables or concepts and developing hypotheses to test and verify those relationships, the result of such verification could be a modification of an existing theory (Al-Ababneh, 2020; Sekaran & Bougie, 2010). For instance, in the case of healthcare professionals who are using IoMT continuous collection of data results in identifying variables that are related to each other. For example, if IoMT is being used to support patients in ensuring continuous monitoring of their healthcare parameters then such monitoring could lead to its continuous usage. However, in the case of the inductive approach, the researchers usually discover theories and believe that the relationship between two variables is less important in comparison to other reasons that cause variation (Sekaran & Bougie, 2010). For instance, if the researcher adopts an inductive approach to determine why or why not healthcare professionals intend to continuously use IoMT, then instead of focusing on the relationship between intention to continuously use IoMT and usefulness, they may find other reasons that could be the cause of using or not using IoMT. In this situation, the researcher may find that the motivation or attitude of healthcare professionals could be the reasons and either establish a new theory by exploring the motivation and attitude of healthcare professionals or bring a theory which is very similar to an existing theory. Adoption of either of the approaches depends on the nature of the problem being studied by the researcher. While inductive research is usually associated with interpretive research philosophy, subjective ontology and qualitative method, the deductive approach is associated with positivist research philosophy, objective ontology, and quantitative method (Holden & Lynch, 2004). Both inductive and deductive approaches have limitations. For instance, the deductive approach is criticised for its tendency to construct a rigid methodology that doesn't allow an alternative explanation of what is happening (Saunders et al., 2016). However inductive approach is criticised for being a less structured approach (Shin, 2019; Saunders et al., 2016), which could lead to a less accurate conclusion about the phenomenon that is under investigation. After discussing the approaches that could be adopted by researchers. Next section discusses the research methods that are widely adopted in the literature.

4.5. Research methods

Widely used research methods include qualitative and quantitative research methods (Sekaran & Bougie, 2019). Literature shows that the use of quantitative or qualitative research methods is prevalent in investigations in the field of healthcare including those concerning IoMT (Heinsch et al., 2021; Alanazi & Soh, 2019). However, the following discussions on these two methods will reveal how to choose the most appropriate reach method for any research.

4.5.1. Qualitative and Quantitative methods

Quantitative research is framed in terms of using numbers and is the most dominant research method in social sciences and management sciences research (Creswell & Creswell, 2018).

According to (Creswell & Creswell, 2018), quantitative research is characterised by the following:

- It is used to test objective theories
- Testing of those theories is usually conducted for examining relationships among variables
- Those variables could be measured typically on measuring instruments that collect numbered data.
- The numbered data could be analysed using statistical procedures.
- Researchers using quantitative research methods have assumptions about testing theories using a deductive approach.
- Usually, researchers using quantitative research establish protections against bias, control for alternative explanations and generalise findings that could be replicated.

For instance, understanding the diffusion of IoMT could be achieved using quantitative research methods through the process of testing the diffusion of innovation theory (DOI). While doing so the relationship between diffusion of innovation variables namely relative advantage, complexity, compatibility, trialability and observability are tested for their relationship with other variables depending on the context, for instance, the continuous intention of healthcare professionals to use IoMT (Al-Rahmi, et al., 2019; Lee, et al., 2011). Further, quantitative research methods are grounded on positivist epistemology and objective ontology (Holden & Lynch, 2004). The use of the quantitative research methods depends on the research question which requires examining the relationship between variables through surveys and experiments. Usually, statistical analyses of data provide the basis for testing theory and such data are objective in nature, collected through empirical observations. An important aspect of quantitative research is that it uses correlational and causal-comparative approaches focus on the reliability and validity of collected data (Creswell & Creswell, 2018).

Examples of research using quantitative methods include survey design and experimental design (Creswell & Creswell, 2018). The strength of quantitative research methods includes the comparison of results, replication of research, verification of assumptions using statistical tools, generalisation of findings, absence of researcher bias, independent of study settings and verification of reliability and validity of the analysed data (Creswell & Creswell, 2018). Weaknesses include rigidity, inflexibility, lack of consideration of the experience of respondents, and dependence on the beliefs, theories and law like conclusions drawn for application in the real world (Saunders et al., 2019). Quantitative research methods are widely used in IoMT research, diffusion of innovation studies and behavioural intention to adopt studies (Rajmohan & Johar, 2020).

4.5.2. Qualitative studies

According to (Creswell & Creswell, 2018), qualitative studies involve topics where inquiry revolves around questions namely who and what, and user's verbs such as explore, understanding or discover. For instance, in the current research, there could be inquiries about how diffusion of IoMT takes place and what factors need to be explored to understand such a diffusion (Gatouillat et al., 2018). Qualitative research the primary instrument is the researcher himself or herself who is used for data collection and analysis (Campbell, 2015; Hancock & Algozzine, 2017). Literature shows that qualitative research methods are associated with interpretive research philosophy, subjective ontology and inductive research approach (Creswell & Creswell, 2018; Kaushik & Walsh, 2019). Some of the advantages as identified by researchers including Eyisi (2016), Leedy & Ormrod (2014) and De Vaus & de Vaus (2013) and limitations identified by researchers including Hammarberg et al. (2016), Eyisi (2016) and Myers (2000) concerning qualitative research method are tabulated in table 4-1.

Table 4-1:Qualitative research method: advantages and limitations

#	Advantages	Limitations
1.	Its ability to characterise research as meanings, a concept, a definition, a metaphor, symbols and descriptions of things.	Limitation of the findings of the research to a particular group of people being studied leads to a lack of generalisation.
2.	Providing a wider understanding of behaviour of the people.	Lack of reflection of the findings to a wider population
3.	Providing a large quantum of data about the real life of people and situations.	Lack of replicability
4.	Collected data is unique.	Lack of reliable and constant data
5.	Led to the emergence of theory from data collected.	Possibility of the researcher being wrong, inaccurate and misleading due to the employment of subjective methods.
6.	Allowing researcher to construct and reconstruct theories, when necessary, based on the data the researcher generates.	Research outcome can't explain findings as the research is exploratory nor explanatory
7.	Examination of phenomenon in depth.	Difficulty in simplifying findings and observation as the results or based on the interpretation of the researcher at a particular point in time thereby lacking repeatability of the research at another place and another instant of time.
8.	Use of multiple methods including observation, open under question in depth interview, case study, grounded theory, ethnography and action research	

Although qualitative research methods are characterised by limitations, their advantages have encouraged the researcher to use it in research concerning the diffusion of innovation, IoMT, motivation, training and behavioural intention to adopt studies (Smirnova et al., 2021; Peng et al., 2016). As far as the current research is concerned it can be seen that the research questions are dealing with "to what extent diffusion of innovation factors influence continuous intention to use IoMT regarding the context of a healthcare professional. This statement clearly points toward the inability of the qualitative research methods to support the researcher in answering the research question because the research questions don't address how and what way the DoI of IoMT affects continuous intention to use IoMT. After critically reviewing the literature on the epistemological, ontological, approaches research and methodological aspects the researcher is now able to define the research framework discussed next.

4.6. Research framework

The research framework is a guide for the researcher and indicates what to include in the research, how to perform the research and what interpretations need to be derived based on the analysis of collected data. Within this framework, the research process was conducted with the final objectives of managing the data and ways to communicate the findings (Kivunja, 2018). In essence, the process of collecting, analysing and interpreting data to gain knowledge about a phenomenon is embedded in the research framework. For instance, concerning understanding the use of IoMT, the researcher aims to collect, analyse and interpret data using quantitative research methods. The justification for using quantitative research methods could be provided by analysing the research question which aims to understand the extent to which diffusion of innovation factors influences the continuous intention to use IoMT. This statement analyses the question of the extent to which DoI factors influence continuous intention to use IoMT.

Any research question that addresses how much of a phenomenon is associated with quantitative research methods. In this research, the use of a qualitative research method can't be justified as the research doesn't investigate the question of 'how' (Creswell & Creswell, 2018). Therefore, as part of the framework, the quantitative research method has been chosen for this research. Further, the justification for the choice of the research philosophy, ontology and the research approaches have been provided next which form part of the research framework.

1- Quantitative research method is directly linked to the deductive research approach, objective ontology and positivist research philosophy.
2- The choice of positivism as the philosophy is attributed to the fact that continuous intention to use IoMT is a reality and can be explained by law like generalisation. This statement is supported by the literature review (chapter 2).
3- The choice of objective ontology can be justified by the fact that the central issue of this research namely continuous intention to use IoMT while IoMT is still diffusing is assumed to be the reality that exists independent of the researcher. This means that the phenomenon of continuous intention to use IoMT occurs regardless of the number of healthcare professionals managing or using it and while it is still diffusing in the market.

4- This can only happen if the phenomenon is investigated with the application of objective ontology which doesn't depend on such aspects as feelings, perception and experience of the researcher in regards continuous intention of the healthcare professionals to use IoMT. In addition, since objective ontology is linked to positivist philosophy and quantitative research method, the justification regarding the choice of the objective ontology is further strengthened.
5- Since positivism is also associated with the quantitative research methods the choice of positivism as the research philosophy could be justified.

After determining the research framework, the next step taken involved defining the research design for this research which describe next.

4.7. Research design

According to literature search design involves rational decision-making choices. In this research, the decisions made by the researcher were associated with the following (Sekaran & Bougie, 2019):

The type of the study is correlational as the research is aiming at delineating important variables related to continuous intention to use IoMT. In addition, this study attempts to understand the cause-and-effect relationships through correlational analysis as well as path analysis. Further, the purpose of the study was hypothesis testing aimed at understanding the phenomenon of continuous intention to use IoMT usage at generating additional knowledge. Next, this research was conducted in non-contrived settings, for example, hospitals, so that the research is actually conducted in a natural environment of the organisation where the work process takes place in a normal setting. The time horizon of the study was cross-sectional as the data will be collected only once. This is in line with other researchers (e.g., Al-Rahmi et al., 2019; Baudier et al., 2019) who have conducted similar research and were able to answer the research questions using cross-sectional research. The researcher conducted the study in a natural environment where the researcher did not have any interference with the normal flow of work. The unit of analysis for this research was a healthcare professional using or desiring to use IoMT continuously to support patients and provide better healthcare to them. Since the number of healthcare professionals associated with continuous intention to use IoMT is running in its thousand's, sampling design was used to complete the research within the time frame available to complete this research. This is a usual practice used in empirical research (Saunders et al., 2019). After discussing the various steps involved in the research design, the next section discusses the research strategy used in this research.

4.8. Research strategy

The choice of the research strategy depends on the research questions to be answered in this research. The research questions are concerned with the diffusion factors that influence the continuous intention of the healthcare professionals to use IoMT, behavioural attributes of the healthcare professionals that act as moderators in the relationship between DoI factors and continuous intention to use IoMT and moderators of the relationships between DoI factors, mediators and the dependent variable. This involves the study of the healthcare professionals in a healthcare setting. It was necessary to collect data from those professionals to test the hypotheses developed for this research and the research model (see figure 3.7). Primary data was to be collected from the healthcare professionals. Primary data is the one collected using a self-administered research instrument while secondary data is the one that exists already and there is no need for researchers to collect fresh data (Sekaran & Bougie, 2019). Amongst the two methods suggested in the literature to collect primary data namely experimental and survey research, in this research the survey research method was chosen. This is in line with similar research conducted by other researchers. For instance, Hasan et al. (2021) while investigating young physicians' intention to use the Internet of Things (IoT) services employed a survey research method. Similarly, Jaafreh (2018) while studying the adoption of internet of things (IoT) technology in the SME in KSA used a survey strategy while collecting primary data. There are examples of other authors who have used a similar strategy in studying continuous intention to use IoT in multiple contexts including healthcare (Al-Rahmi et al., 2019; Baudier et al., 2019; Alalwan et al., 2018). The reason for not choosing the experimental method was that the study requires data to be collected from the healthcare professionals in their natural work setting that is not under the control of the researcher and not in a laboratory setting where a controlled environment is made available for research. Moreover, the survey method helps in answering questions like ‘what’, ‘who’, ‘where’, ‘how much’ and ‘how many’ (Saunders et al., 2019). As far as the place of research was concerned, the research was conducted in Bahrain. The research was conducted over a period of three months at the peak of the COVID-19 period in 2020. Several hospitals were approached in Bahrain to collect data from healthcare professionals. The data was collected using a Likert scale type research instrument that was designed for this research.

4.8.1. Research instrument used in the survey to collect data

A survey research instrument is a tool used by researchers to elicit responses from the participants in the survey (Sekaran & Bougie, 2019). This instrument is a pre-designed set of statements with closely defined alternatives. Some of the benefits of survey instruments include a direct and quick collection of information about attitudes, behaviours, characteristics and opinions of respondents, availability of first-hand data for use in empirical research, possible use of measurement scales, facilitation of analysis of collected data through statistical procedures to extract value and development of a reliable instrument based on many factors, classical models and theories (Lu et al., 2021). It is also possible to administer the instrument efficiently to the participants over e-mail, through web postings and through direct contact (Saunders et al., 2019; Radaelli & Fritsch, 2012; Glasow, 2005). Questionnaire-based surveys are one of the most widely used methods in quantitative research (Zhu et al., 2018; Sanchez-Gordon & Lujan-Mora, 2017). Moreover, quantified and objective information was needed for this research as a source of data regarding a particular population (Ticehurst & Veal, 2000) namely healthcare professionals either using IoMT or likely to use IoMT from the hospitals in Bahrain.

There are limitations to administering the survey. These include the possibility of a lower response rate and small sample sizes that could be accessed during data collection, lack of diversity amongst participants, limitations in statistical analysis (Lu et al., 2021), inhibition of deeper enquiry, lack of an ability to capture abstract aspects of human experience and perception, such as hope or uncertainty, involves risks of underreporting or reporting bias, and raises ethical concerns (Boyden et al., 2021). Despite limitations, the researcher adopted the survey instrument strategy to conduct the research by taking precautions about the limitations. The strategy adopted was that a pilot test was conducted to test the reliability and validity of the instrument initially before the main survey was conducted.

4.8.2. Development of the survey instrument

In this research for the pilot survey the questionnaires were administered personally as the number of respondents approached was small while for the main survey Google Forms was used. Cresswell and Cresswell (2018) suggest that the development of a survey instrument needs careful attention to many details which include:

- Whether the instrument is going to be newly developed to specifically address the requirements of a researcher or adapt already developed instruments that could be useful for the purpose of the current research.
- Reliability and validity aspects whether having been already established by previous researchers or have to be tested
- Information about the sample group of respondents on whom the research instrument will be served.
- Information about the contents of the instruments including sections to be used scales to be adopted and the introductory note to be attached to the instrument.
- Strategy to administer the instrument.

In addition to the above Sekaran and Bougie (2019) and Zikmund (2003) suggest the following criteria to be followed while developing the instrument:

- Grouping the variables in the instrument.
- Wordings to be used as part of the statements to which responses are going to be solicited.
- General appearance of the instrument.
- Ensure that the statements are able to generate data that can be sued to answer the research question and objectives.

The instrument was designed using the already developed instruments by other researchers who have measured the variables under consideration in the research model (see figure 3.7). The details of the items used to measure the variables and the authors from whose research work the items have been extracted and adopted for this research are provided in Appendix 6. The items and the scales used for this research have been already tested for their reliability and validity by those researchers whose work the items have been culled out.

The adaptation was required as the theoretical model developed for this research is unique and the items were adapted based on the concepts that have been used in the conceptual model to define the variables (see figure 3.7) and the relationships between those variables that have been developed. In addition, the extracted items were modified to suit the requirements of this research taking into account the research questions set for this research, hypotheses and the population under study. The conceptual model has integrated theories and concepts already developed by other researchers and hence it was logical to extract certain items related to the measurement of those concepts for use in this research as those items and the measuring scales have been tested for their reliability and validity already. All items were drafted in the English language and were carefully worded so that the respondents who participated in the survey will not face any constraints while responding to the survey items. Care was taken to minimise any bias while designing the instrument. In addition, although the local language is Arabic, in the healthcare industry in Bahrain where the research was conducted, a multicultural environment exists and hence the instrument was worded in English. In addition, the healthcare sector is characterised by employees who belong to different nations and occupy positions at multiple levels and the education levels are generally high. Combined with this feature is the high level of English used in the healthcare sector in Bahrain regardless of nationality. Those professionals were expected to understand the simple language in which the items were constructed for measuring the constructs. Thus, English is the common language used in healthcare organisations in Bahrain. The use of English also helped in retaining a major portion of the instruments and the exact meaning of the terms required to be conveyed to the participants as translation might alter the meaning. Minor modifications in those items helped in generating a clean instrument that could be used in the survey.

The instrument was designed to comprise two sections. The first section comprises items related to the demographic aspects of the respondents while the second section is concerned with the measurement of the variables. An introductory note was presented at the beginning which informs the participants about the various aspects of the data collection aspects. This information included an introduction to the survey, objectives of the survey, an explanation about the PhD study at Bradford University, UK, about the anonymity as well as confidentiality that will be maintained and that the data will be used solely for the purpose of this research. This information is provided in Appendix 7.

Section 1 dwelt on descriptive statistics related to the respondents' data. Data related to gender, age, employment details, income category in which the respondent would be placed, level of education qualification and the usage of IoMT were collected through this section. Section 2 is the main section and was devoted to a variable measurement. This consisted of 49 items that were used to measure the independent and dependent variables Appendix 8. A 5-point Likert scale was used in Section 2. Likert scale is a widely used scale to measure opinions and attitudes of people like 'not committed' to 'very committed' or 'very similar' to 'very different'. A summary of the scales used is provided in table 4-2.

Table 4-2: List of variables used in the research

#	Variable name	Variable type	Number of items used to measure the variable
1.	Relative advantage	Independent	6
2.	Complexity	Independent	4
3.	Compatibility	Independent	4
4.	Trialability	Independent	4
5.	Observability	Independent	4
6.	Motivation	Mediating	5
7.	Training	Mediating	5
8.	Continuous intention	Dependent	4
9.	AI Awareness	Moderating	6
10.	Novelty seeking	Moderating	6
11.	Age	Moderating	1

The items were measured using 5-point Likert scales with 1 indicating ‘strongly disagree’ 2 indicating ‘disagree’, 3 indicating ‘neutral’, 4 indicating ‘agree’ and 5 indicating ‘strongly agree’. Table 4-3 lists the items used to measure the variables. Further to the development of the survey instrument, a pilot survey was conducted to check the initial validity of the instrument and see whether any improvements are needed with regard to the statements, the language used to construct the statements, format and scales used (Creswell, 2014). The pilot survey is a small-scale trial of the main survey and is conducted on a sample of the actual population under study. Another important reason for conducting the pilot survey is that the instrument could be refined further, to reduce problems for the participants in responding to the survey (Saunders et al., 2019). The pilot survey was conducted by distributing the research instrument through e-mail to about 50 healthcare professionals in healthcare organisations in Bahrain.

4.8.3. Choice of the territory to conduct the research

The research was conducted in healthcare organisations in Bahrain. The use of IoMT in those healthcare organisations in Bahrain is on the rise and the intention to use IoMT for those professionals in Bahrain is a concept still not investigated. The population of 1.4 million people (General Directorate of Statistics & Population Registry, 2017) in Bahrain are served by both private and public healthcare organisations to ensure that the citizens are provided with the best medical care. The technological advances taking place in Bahrain can be understood by the fact that Bahrain is ranked 38 at the global level, ranked 2nd at the Arabic regional level, in regard to the e-government development index (EGDI) announced by United Nations in 2020 indicating that the online usage in Bahrain at the government level is very high. In addition, the percentage of individuals using the internet in Bahrain was measured by the UN as 98.64% which is one of the highest penetrations of the internet in the world with only three other countries being ahead of Bahrain in this category (UN, 2020). As far as the healthcare facilities are concerned Bahrain boasts of well-equipped hospitals both in the private and public sectors. Table 4-3 shows the statistics about the healthcare organisations available in Bahrain.

Table 4-3: Healthcare resources available in Bahrain

#	About the healthcare resources	Numbers
1	Registered healthcare facilities (at the end of 2019) (NHRA, 2019)	746

2	Physicians (at the end of 2016) (NHRA, 2016) which includes	4111
	2a. General doctors	3030
	2b. Consultants	704
	2c. Specialists	377
3	Dentists	437
4	Nurses (includes general nurses, midwives, specialist nurses and pediatric nurses)	8962
5	Pharmacists (NHRA, 2016)	1228

4.8.4. Challenges faced in data collection due to COVID19

As far as the internet of medical things is concerned, Haji (2018) argues that they are already being used in Bahrain and cites examples of wearables being used by citizens and tracked by healthcare professionals. Another example is the mobile application named 'BeAware Bahrain' launched by the Government of the Kingdom of Bahrain, which alerts people who are in the proximity of COVID-19 infected people and is also used to track the self-isolated people by identifying their location. This also indicates the location-based service given through IoMT by the Government of the Kingdom of Bahrain. The system of medical services and standards used in Bahrain is very similar to NHS, UK. Thus, Bahrain provided the support to conduct this research.

The Coronavirus outbreak during the period of conducting this research was a major challenge encountered by the researcher while collecting the data. The data was collected during the period July 2020 - August 2020 when COVID-19 was at its peak throughout the Kingdom of Bahrain. At that time the government of the Kingdom of Bahrain recommended that going to a hospital was not advisable, not only for urgent and life-threatening situations but also for check-ups and patient visits. At this critical juncture visiting hospitals and having discussions with the staff to collect data for the research was not possible. A strategy was therefore needed to approach healthcare organisations to collect data. Hospitals shortlisted that were using IoMT and details like names and phone numbers of those hospitals were found out and documented. The hospitals were contacted over the phone and emails were sent to the administrators of many public and private hospitals to inform them of the significance of the research and get permission to collect data. The permissions were not easily forthcoming, and the pandemic was spreading fast.

After struggling to communicate with the public and private hospitals, after several attempts it was possible to get in touch with the people concerned and obtain their consent to collect data. With the exception of one government hospital, which declined to cooperate due to the emergency situation that prevailed at that time (the hospital was labelled as a quarantine centre for COVID-19), patients and other hospitals allowed data collection through e-mail.

The hospitals appreciated the study and instructed that the questionnaire had to be delivered electronically which led the researcher to use Google Forms. The developed instrument was distributed through the healthcare organisations' official emails and social media channels as also communication directors in hospitals and other healthcare facilities. This enabled the researcher to have effective communication to collect data that was reliable.

The hospitals that were approached included amongst others were King Hamad Medical Hospital, Ibn Al-Nafis Hospital, Al-Zeera Medical Center, Dr. Moneam Hafada Center, Salmaniya Hospital, Al Hillal Hospital and Dr. Tariq Saeed Hospital. This struggle enabled the researcher to overcome the challenge of COVID-19 and collect data for this research.

4.9. Pilot study

A pilot study was conducted by distributing the survey instrument to 50 healthcare professionals working in different healthcare organisations. In this research, the definition of a healthcare professional adopted was the one defined by the National Health Regulatory Authority (NHRA) (2017). Kingdom of Bahrain, which says “A person who by education, training, certification and licensure is qualified to provide healthcare services”. Examples of healthcare professionals have been provided in table 4-3. Since the research was conducted in Bahrain and the license to practice in the healthcare sector is given by the Government of the Kingdom of Bahrain the definition of the healthcare professional given by NHRA was adopted in this research. There is no specific rule or formula that is suggested in the literature regarding the sample size that needs to be used in a pilot study concerning research in the management discipline. For instance, Cooper and Schindler (2011) suggest a sample size that lies between 25 and 100 subjects while others (Hill, 1998; Isaac & Michael, 1995) have suggested a range of 10-30 subjects. Connelly (2008) suggests a number that is 10% of the sample project for the main survey. Additionally, Cooper and Schindler (2011) suggest that the sample size selection should be decided on the type of analysis at the pilot survey stage. Based on the discussions given above it can be concluded that a choice of 50 healthcare professionals to participate in the pilot study is reasonable. Thus, data were collected in August 2020 through the pilot survey from amongst the healthcare professionals mentioned in table 4-3. 38 valid responses were received. The pilot study provided the basis for determining the reliability and validity of the survey instrument which are discussed next.

4.9.1. Pilot study results

SPSS software version 21 was used to conduct the preliminary analysis of the data collected through the pilot study. Preliminary data analysis included checking the mean, standard deviation, reliability and validity of the data. 5-point Likert scale provided ordinal data that could be used to compute the statistical analysis Appendix 9. Following the descriptive reliability, validity analysis was conducted.

4.9.2. Reliability analysis

According to Heale and Twycross (2015) explain that reliability of a survey instrument indicates the consistency of a measure. That is to say, if a researcher is measuring relative advantage with an instrument meant to measure the construct, then this instrument when used again should generate approximately similar responses each time the test is conducted. However, Ticehurst and Veal (2000) argue that reliability is a test which informs the researcher whether the research could be repeated with the same instrument at a later date or with different samples within the same population. One of the most widely used measures of reliability in empirical research is Cronbach’s coefficient alpha (Heale & Twycross, 2015). While there are other methods that are suggested in the literature that can be used to measure the internal consistency that including Split-Halves Test and Kuder-Richardson Test most researchers use Cronbach’s alpha as the reliability measure. The reason is the disadvantages associated with Split-Halves Test and Kuder-Richardson Test. For instance, split-halves test results might not accurately represent the internal consistency of all research trials for instance the measurement of relative advantage (Clayson et al., 2021) while Kuder-Richardson Test suffers from the limitation that the responses to the statements in the instrument must be simple like the binary response namely right or wrong (Wombacher, 2017). As far as Cronbach's alpha is concerned it suffers from some limitations. For instance, in a survey individual could provide the same responses to all the items without reading the items carefully. This could lead to inflated estimates of the reliability arising out of the similarities that have existed between scores on the items (Johnson, 2017). Despite the limitations attributed to Cronbach's alpha, researchers have widely used it as the reliability measure in empirical studies in many fields including the diffusion of the internet of medical things due to the overwhelming advantages it offers (Berg et al., 2018; Boessen et al., 2017; Rho et al., 2015; Vanneste et al., 2013).

Cronbach's alpha was measured using SPSS software version 21. Alpha is measured as a number that lies between 0 and 1. Cronbach's alpha equal to or greater than 0.7 is considered to be sufficiently high in reliability (Johnson, 2017). Values of alpha approaching 1 indicate greater reliability and higher internal consistency. However, it must be mentioned here that there is no consensus amongst researchers about whether values of alpha less than 0.7 as reliable or not (Nawi et al., 2020). For instance, researchers (e.g., Straub et al., 2004; Hinton et al., 2004) classified Cronbach's alpha as excellent reliability (alpha > 0.9), high reliability (alpha > 0.7 but < 0.9), moderate reliability (alpha > 0.5 but < 0.7) and low reliability (< 0.50). However, Taherdoost & Group (2017) argued that for the pilot study an instrument is considered reliable if the alpha value is measured as ≥ 0.6. Finally, very high values of alpha approaching 1.0 could also be problems as it may indicate items measuring a construct could be redundant (Nawi et al., 2020). Taking the above arguments into consideration in this research to measure the reliability Cronbach's alpha measuring ≥ 0.7 was set as the reference value. The results of the pilot study related to reliability have been provided in table 4-4.

Table 4-4: Preliminary analysis of reliability and validity before deleting items

#	Construct	Code	No. of items	Items	Cronbach's Alpha (≥0.7)	Item-item correlation (≥0.3)		Item-total correlation (≥0.5)		Remarks
						Min.	Max.	Min.	Max.	
1	Continuous intention to use	CI	4	CI1-CI4	0.892	0.571	0.816	0.678	0.857	Accepted
2	Relative advantage	RA	6	RA1-RA6	0.951	0.599	0.932	0.769	0.893	Accepted

3	Complexity	CPX	4	CPX1-CPX4	0.800	0.326	0.738	0.559	0.716	Accepted
4	Compatibility	CMP	4	CMP1-CMP4	0.772	0.358	0.615	0.509	0.615	Accepted
5	Trialability	TRI	4	TRI1-TRI4	0.718	0.105	0.547	0.35	0.715	Some items causing concern
6	Observability	OBS	4	OBS1-OBS4	0.822	0.434	0.695	0.577	0.725	Accepted
7	Motivation	MOT	5	MOT1-MOT5	0.829	-0.015	0.749	0.427	0.838	Some items causing concern
8	Training	TRN	5	TRN1-TRN5	0.899	0.469	0.876	0.697	0.781	Accepted
9	AI Awareness	AWS	6	AWS1-AWS6	0. 851	0.17	0.777	0.288	0.842	Some items causing concern
10	Novelty seeking	NS	6	NS1-NS6	0.801	-0.063	0.815	0.122	0.795	Some items causing concern

It can be seen that the range of Cronbach’s alpha for the constructs continuous intention to use, relative advantage, complexity, compatibility, trialability, observability, motivation, training, AI awareness and novelty seeking was found to lie between 0.718 and 0.951 indicating acceptable reliability. Thus, it was concluded that at the pilot study stage the research instrument used in the survey was considered to be reliable and ready for use in the main survey.

4.9.3. Validity

The test of validity is a statistical measure which indicates the degree to which a construct representing a concept is measured accurately (Heale & Twycross, 2015). For instance, in this research, the instrument developed for measuring relative advantage has six items namely RA1 to RA6. Validity refers to the accuracy with which the six items measure the construct's relative advantage. Sekaran and Bougie (2019) argue that four different types of validity measures are used in empirical research including content validity, criterion-related validity, discriminant validity and construct validity. It is important to note that both reliability and validity measures apply to both pilot and main surveys. However, when measured at the pilot survey stage, both reliability and validity measures ensure that if there are any shortcomings in the research instrument concerning such aspects as content, wordings, language, format and scale used, found at this stage could be addressed before the main survey. Thus, at the pilot survey stage, the researcher gets a good opportunity to discover problems regarding content, wordings, language, format and scale used in the instrument. If the shortcomings are not addressed at this stage, it is possible that in the main survey stage the researcher could face difficulties due to those shortcomings and resolving such difficulties may not be easy as it might be too late to resolve those difficulties. Each one of the four validity measures are described next.

4.9.4. Content validity

Content validity also termed face validity refers to the examination of the contents of the instruments by experts in the field in terms of the association between the individual items and the concept under measurement (Hair et al., 2019). The instrument was checked with regard to the contents of the items used to measure the various constructs as well as the correspondence between the items and the construct through ratings by experts in the field of intention to use technology and IoMT. Four experts were approached that is an expert in the field of intention to continuously use technology, an academic, a researcher in the field and a healthcare professional. Minor revisions were made to the content in terms of wording and format after getting feedback from the experts. Thus, the content validity was tested at the pilot survey stage.

4.9.5. Criterion validity

Criterion validity is the same as convergent validity (Quinlan et al., 2019) and is the correlational analysis between items. Hair et al., (2019) explain that convergent validity is a measure which shows that indicators of a particular construct (items used to measure the construct) must converge or have a high proportion of variance in common. That is to say that this indicates the extent to which two items measuring a construct are correlated. Correlation indicates a statistical relationship between two variables (e.g., between items measuring a construct or between two constructs) but does not suggest that one variable causes change in the other variable (Sekaran & Bougie, 2019). The high correlation between items measuring a construct indicates that the scale used to measure the items measures the construct. Thus, reliability is an indicator of convergent validity (Hair et al., 2019) as internal consistency measures the correlation between the items. Cohen (1988) classifies the correlation measurements as small, medium and large correlations (symbol ‘r’). Small correlation indicates a correlation range of 0.1 - 0.29 between items or constructs. Medium correlation indicates a correlation range of 0.3 - 0.49 between the items or constructs and a large correlation indicates a correlation ≥0.5 but ≤1.0 (Cohen, 1988). The acceptable value of correlation cited by Nawi et al., (2020) between variables (item to item correlation) is ≥0.3 and item to total correlation is ≥ 0.5 (Robinson et al., 1991a). Convergent validity is said to be achieved if the item-to-item correlation is found to be ≥0.3 while item to total correlation is found to be ≥0.5. While item to item correlation indicates the relationship between two items measuring a construct (example RA1 and RA2), item to total correlation measures the correlation between an item and the rest of the items that measure the construct. From table 4-5. it can be seen that the item to item and item to total correlation values for the construct's continuous intention to use, relative advantage, complexity, compatibility, observability and training were found to be ≥0.3 and ≥0.5 respectively. This indicates that the convergent validity of these constructs has been achieved at the pilot study stage. However, the item to item and item to total correlation values for the constructs trialability, motivation, AI awareness and novelty-seeking were found to be ≤0.3 and ≤0.5. This indicated that some items measuring these constructs were causing concern leading to lower values of the item-to-item correlation and item and total correlation. It was found through the correlation analysis that TRI was causing concern in not achieving the item to item and item to total correlation values for the construct trialability while MOT1, AWS6 and NS5 were causing correlation concern for the construct's motivation, artificial intelligence awareness and novelty seeking. These items were excluded from the instrument. The item to item and item to total correlations were measured again for those constructs namely trialability, motivation, training, AI awareness and novelty seeking. Table 4-5 shows that after excluding the items causing concern, the item to item and item to total correlation values were found to be ≥0.3 and ≥0.5 respectively for the constructs trialability, motivation and artificial intelligence awareness.

Table 4-5: Preliminary analysis of reliability and validity after deleting items.

#	Construct	Code	No. of items	Items	Cronbach's Alpha (≥0.7)	Item-item correlation (≥0.3)		Item-total correlation (≥0.5)		Remarks
						Min.	Max.	Min.	Max.	
1	Continuous intention to use	CI	4	CI1-CI4	0.892	0.571	0.816	0.678	0.857	Accepted

2	Relative advantage	RA	6	RA1-RA6	0.951	0.599	0.932	0.769	0.893	Accepted
3	Complexity	CPX	4	CPX1-CPX4	0.800	0.326	0.738	0.559	0.716	Accepted
4	Compatibility	CMP	4	CMP1-CMP4	0.772	0.358	0.615	0.509	0.615	Accepted
5	Trialability	TRI	3	TRI2-TRI4	0.729	0.412	0.583	0.469	0.604	TRI1 causing concern. TRI1 has been deleted
6	Observability	OBS	4	OBS1-OBS4	0.822	0.434	0.695	0.577	0.725	Accepted
7	Motivation	MOT	4	MOT2-MOT5	0.852	0.44	0.749	0.571	0.857	MOT1 causing concern. MOT 1 has been deleted
8	Training	TRN	5	TRN1-TRN5	0.899	0.469	0.876	0.697	0.781	Accepted
9	AI Awareness	AWS	5	AWS1-AWS5	.886	0.468	0.777	0.603	0.838	AWS6 causing concern. AWS6 deleted
10	Novelty seeking	NS	5	NS1-NS4 &NS6	0.84	0.244	0.815	0.425	0.8	NS5 causing concern. NS5 deleted

But the item to item and item to total correlation values for the construct novelty-seeking was found to be ≤0.3 and ≤0.5 respectively. However, no further items were excluded from the instrument in order to improve the item to item and item to total correlation values for the construct novelty seeking as such a situation could occur due to a lower sample size and in the literature, it has been pointed out that correlations between items or constructs depend on sample size (Bujang et al., 2018). That is to say that the higher the sample size better will be the correlation. Therefore, at this stage of the pilot survey even though the item to item and item to the total correlation of the construct novelty seeking were found to be ≤0.3 and ≤0.5 respectively, it was decided to retain the remaining items and the items were except NS5. The items measuring novelty seeking were retained and kept under observation so that items (NS3-NS6; correlation 0.244) creating any concern could be dealt with using a larger sample size that was to be collected through the main survey. Thus, it can be seen that the convergent was the validity of almost all the constructs was construed to have been achieved at the pilot study stage.

4.9.6. Discriminant validity

Sekaran and Bougie (2019) define discriminant validity as a condition when two variables are predicted to be uncorrelated, and the values derived through statistical measures through empirical research indeed are found to be so. Further, discriminant validity is shown to be measured by correlational analysis (Sekaran & Bougie, 2019). Quinlan et al. (2019) define discriminant validity as a measure that reflects a low correlation between dissimilar concepts. For instance, the correlation between items measuring relative advantage and motivation should be very low (for example could be lower than 0.1) if discriminant validity is said to be established. Holmes-Smith et al., (2006) argue large correlation between constructs or variables (0.8 or 0.9) indicates a lack of discriminant validity. In addition, average variance extracted (AVE) is another method by which discriminant validity is established (Janssens et al., 2008). The average variance extracted is a Fornell-Lacker criterion that indicates discriminant validity (Ab Hamid et al., 2017; Fornell & Cha, 1994). Discriminant validity is established if variances that are shared by two constructs (squared correlation) should be higher than the average variance extracted from these constructs. There are other methods used to test the discriminant validity including the Fornell-Larcker criterion, cross-loadings, heterotrait-monotrait (HTMT) ratio, and full collinearity assessment (Rasoolimanesh, 2022) However, Fornell-Larcker criterion, cross-loadings, heterotrait-monotrait (HTMT) ratio are metods are argued to be used in research that examines models with reflective constructs whereas full collinearity assessment involves models with formative constructs (Rasoolimanesh, 2022). According to Coltman et al. (2008) a reflective construct is one where a latent construct exists independent of the measures (example attitude and personality). A latent construct is the one, which is indirectly measured and not immediately observable (Janssens et al., 2008) (e.g., relative advantage (RA) in figure 3.7). A formative construct is the one which is formulated through an interpretation of the latent construct and depends on a constructivist, operationalist or instrumentalist interpretation of the researcher (Coltman et al., 2008). A detailed discussion on each one of the methods is beyond the scope of this research as the focus is on the examination of the continuous intention to sue IoMT of the healthcare professionals and not the discriminant validity as a concept.

While different methods have been used to establish the discriminant validity, it can be seen that correlational analysis and average variance extracted methods are widely used in empirical research in management sciences to test for the discriminant validity of instruments as most of the models use reflective constructs (Coltman et al., 2008). In this research, at the pilot stage, the discriminant validity was established using correlational analysis while average variance extracted was used in the main survey analysis. At the pilot stage, it can be seen (from table 4-6) that except for the construct relative advantage where one pair of items (RA2-RA4; correlation 0.932) all other correlations between constructs were found to be less than 0.9. Applying the arguments of Holmes-Smith et al. (2006) which says that any correlation between items that is less than 0.9 indicates that discriminant validity is achieved, it is concluded here that except for the items RA2 -RA4, discriminant validity has been achieved for the rest of the items. This pair of items was under observation for their performance during the main survey and retained to see whether it still causes concern concerning the discriminant validity of these items when the method of average variance extracted was used. Average variance extracted was not used at the pilot stage as it depends on sample size and at the pilot level the sample size was very low (Ronkko & Cho, 2022).

4.9.7. Construct validity

Sekaran and Bougie (2019) argue that construct validity comprises convergence validity and discriminant validity. Thus, construct validity is said to be established if both convergent and discriminant validity are established. At the pilot study stage, it can be seen that both convergent and discriminant validity have been established. The item-to-item correlation and item to total correlations have been tested for all constructs and the items that measure them and it was found that the values measured meet the minimum criteria set for this research (section 4.9.2).

4.9.8. Summary of the result of the pilot survey

The foregoing discussions have shown that at the pilot survey stage the research instrument developed for collecting data required adjustments in terms of removing items TRI1, MOT1, AWS6 and NS5 that the reliability and validity of the instrument could be established. There were minor concerns of discriminant validity related to items RA2 and RA4 and internal consistency related to items NS3 and NS6. These items were kept under observation and were checked for their performance in the main survey where the sample size was higher than in the pilot survey. The content, wordings, language, format and scale used were finalised. Thus, the data collection instrument was finalised for launching the main survey. After discussing the details about the reliability and validity of the instrument at the pilot survey stage the next section dwells on the main survey.

4.10. Main survey

As mentioned in section 4.8.3 the main survey was conducted in Bahrain. The researchers accessed healthcare organisations and approached the healthcare professionals whose list has been provided (in table 4-6).

Table 4-6: List of designations of participants in the main survey

Type of healthcare professionals	Number of participants
Hospital doctors	43
Community Health Services doctors	1
Consultant doctors	48
General practitioners	19
Allied healthcare professional	32
Pharmacist	12
Healthcare scientist (e.g., cervical cytology screener, phlebotomist, newborn hearing screener and healthcare science assistant/associate)	3
Nurses and Health Visitors	131
Ambulance staff	1
Other non-GP Practice staff (direct patient care) (e.g., other staff involved in providing direct patient care, which includes clinical pharmacists, dispensers, phelbotomists, therapists, healthcare assistants and others).	27
Other practice staff (admin) (e.g., Receptionist and administrative staff)	37
Total	354

An overview of the demographics is given in table (4-7).

Table 4-7: Overview of the demographics

Variables	Item	Frequency	Percent
Gender	Male	194	54.8
	Female	144	40.7
	Prefer not to say	16	4.5
Age	18-25	30	8.5
	26-33	124	35.0
	34-41	90	25.4
	42-49	51	14.4
	>50	59	16.7
Educational Qualification	Bachelor's degree	191	54.0
	Master's degree	74	20.9
	Professional certificate	60	16.9
	Doctorate	23	6.5

All the healthcare organisations were provided with the ethical approval granted by Bradford University, which enabled the researcher to mitigate challenges concerning access to come extent. The survey was self-administered and posted online using Google

Forms to collect data. Google Forms offers the facility to conduct an online survey. It was important to use internet-based data collection method due to the prevailing COVID-19 situation as social distancing was very important to be observed. Contact in person was completely avoided with the respondents. Advantages of using Google Forms to collect data through the internet included charting the results or exporting them to spreadsheets for analysis and availability of multiple formats for collecting data to a variety of questions. In addition, it provides custom logic to work through the questions based on answers (Nayak & Narayan, 2019). Other advantages of using the internet to conduct surveys include easy access to new populations, greater generalisation, lower cost of administration, access to a larger sample size and better quality of data (Rice et al., 2017). Although there were possible disadvantages in using the internet to collect data including poor response rates, lack of timeliness, inaccessibility to the internet, lack of computer literacy and difficulties in administering the survey, there is no consensus on the disadvantages affecting the surveys using the internet (Rice et al., 2017; Ficker, 2002). However, care was taken to ensure that the survey does not suffer due to a poor response rate through continuous follow-up with the participants. Healthcare professionals who were using IoMT already or are likely to use IoMT in future were the target population. Various hospitals were approached to collect data from healthcare professionals. The respondents had accessibility to the internet and were using computers regularly for several activities including e-mails, browsing through the net to access information and using applications like MS-word.

4.10.1. Population and Sample size

As mentioned, (in section 4.8.3 and table 4-3), it can be seen that there are over 15,000 healthcare professionals in Bahrain who would be continuously using the IoMT. To collect data from this population for this research, there is a need to adopt a sampling procedure as it is not possible to collect data from each of the subjects belonging to the total population of 15,000 professionals. In such situations, sampling technique could be used to collect data. Sampling is the process of choosing the individuals from an entire population who are considered appropriate to participate in the research as representatives of that population. This process applies to objects and events also

(Sekaran & Bougie, 2019; Sekaran, 2003). Literature shows that sampling techniques can be classified broadly as probability (random) sampling and non-probability (non-random) sampling (Taherdoost, 2016). Each one of these techniques has been subdivided further as shown in figure 4.1.

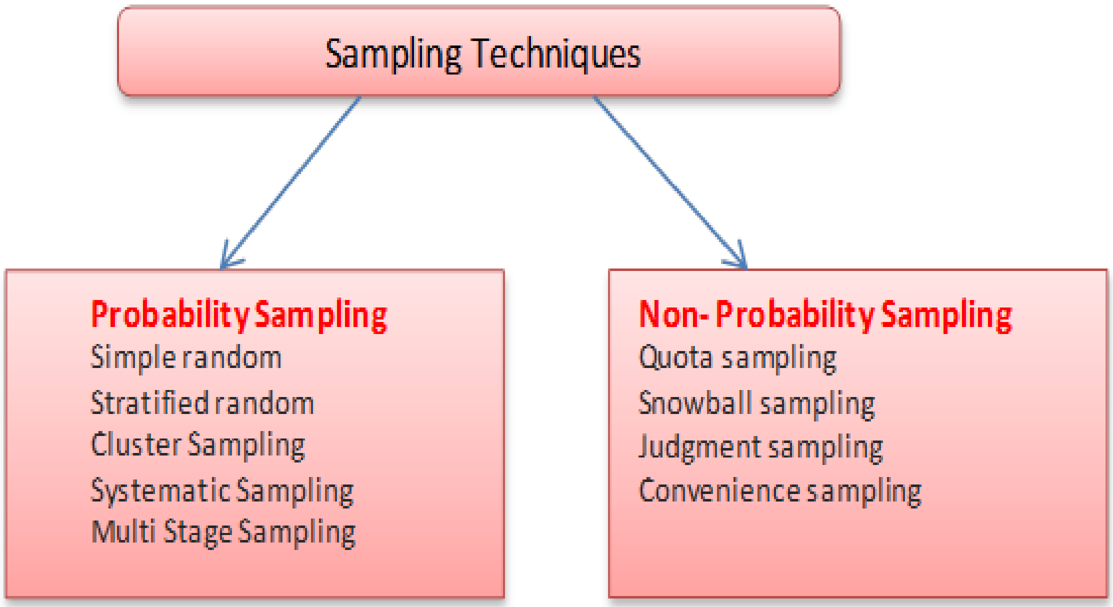


Figure 4.1: Sampling techniques (Taherdoost, 2016)

In probability sampling every element belonging to a population has a known, non- zero chance of being chosen as participants (subjects) in the sample and the results of the research could be generalised and applied to the entire population under study. In non-probability sampling, every element belonging to a population does not have any chance associated with it of being chosen as a sample subject (participant) (Sekaran & Bougie, 2019). A summary of the strengths and weaknesses of the two techniques is provided in table 4-8 (Malhotra and Birks, 2006).

Table 4-8: Strengths and weaknesses of probability and non-probability sampling

Type of sampling	Techniques	Strengths	Weaknesses
Probability sampling	Simple Random Sampling	Easily understood, results projectable	Difficult to construct sampling frame, expensive, lower precision, no assurance of representativeness
	Systematic Sampling	Can increase representativeness, easier to implement than simple random sampling, sampling frame not always necessary	Can decrease representativeness
	Stratified Sampling	Includes all important sub-population, precision	Difficult to select relevant stratification variables, not feasible to stratify on many variables, expensive
	Cluster Sampling	Easy to implement, cost effective	Imprecise, difficult to compute and interpret results
Non-probability sampling	Convenience Sampling	Least expensive, least time consuming, most convenient	Selection bias, sample not representative, not recommended for descriptive or casual research
	Judgment Sampling	Low-cost, convenient, not time consuming, ideal for exploratory research design	Does not allow generalization, subjective
	Quota Sampling	Sample can be controlled for certain characteristics	Selection bias, no assurance
	Snowball Sampling	Can estimate rare characteristics	Time consuming

As far as this research was concerned probability sampling technique was chosen. The reason for that is that probability sampling offers the greatest freedom from bias (Brown, 1947) unlike the non-probability sampling which could be affected by sampling bias (Sharma, 2017). Although probability sampling could be affected by the high cost for a given level of sampling error (Brown, 1947) yet it is considered more accurate than non-probability sampling (Sharma, 2017). For instance, study of the continuous intention of healthcare professionals to use IoMT could involve any of the professionals classified table 4-8. The probability of any of those professionals being selected as a subject can be achieved if those subjects are randomly chosen. This process is expected to be an unbiased representation of the wider population of healthcare professionals as all of those professionals could be studied for the continuous intention to use IoMT regardless of their position or rank. This in turn could enable the researcher to determine the behaviour of the larger population of healthcare professionals.

Furthermore, from amongst the different types of probability sampling techniques identified in figure 4.1 and table 4-8, for this research simple random sampling was chosen because of the advantages it offers over the other types of probability sampling techniques. The random sampling technique is part of the probability sampling method. The current research targeted healthcare professionals working in hospitals in Bahrain who were using IoMT. The number of such professionals working in the whole of Bahrain was in the thousands. There was needed to adopt a sampling strategy. According to Taherdoost (201) probability sampling is best suited if every item in a population has an equal chance of being included in the sample. For instance, in this research, the study was about the healthcare professionals who were using IoMT. The population of healthcare professionals in Bahrain is around 15,000 and comprises a variety of professionals. Therefore, the population from which the researcher had to choose the sample was considered to be 15,000 without having the necessity to pay attention to the type of professional as all of them were using IoMT (which is the mobile application launched by the Government of Bahrain during the prevalence of COVID-19 called "Beware"). Thus, the sampling technique had to be simple random sampling as a chance had to be there for every professional to be included in the survey as other methods do not provide this chance. Thus, in the sense that there has to be a possibility that every healthcare professional has an opportunity to participate in the survey the simple random sampling technique was used. If other sampling techniques had to be considered, then there was a need to identify groups and stratify or cluster the professionals which was not needed. Further to this, the next section determines the sample size required for this research.

4.10.2. Determination of sample size

Sample size was calculated using the sampling table 4-9 generated by Krejecie and Morgan (1970), which provides representative samples for different population numbers. Thus, it can be seen that for a population of 15,000 healthcare professionals, the sample size turns out to be 310.

Table 4-9: Population numbers and sample sizes representing the population (Source: Krejecie and Morgan, 1970)

N	n	N	n	N	n	N	n	N	n
10	10	110	86	300	169	950	274	4,500	354
15	14	120	92	320	175	1,000	278	5,000	357
20	19	130	97	340	181	1,100	285	6,000	361
25	24	140	103	360	186	1,200	291	7,000	364
30	28	150	108	380	191	1,300	297	8,000	367
35	32	160	113	400	196	1,400	302	9,000	368
40	36	170	118	420	201	1,500	306	10,000	370
45	40	180	123	440	205	1,600	310	15,000	375
50	44	190	127	460	210	1,700	313	20,000	377
55	48	200	132	480	214	1,800	317	30,000	379
60	52	210	136	500	217	1,900	320	40,000	380
65	56	220	140	550	226	2,000	322	50,000	381
70	59	230	144	600	234	2,200	327	75,000	382
75	63	240	148	650	242	2,400	331	100,000	384
80	66	250	152	700	248	2,600	335	250,000	384
85	70	260	155	750	254	2,800	338	500,000	384
90	73	270	159	800	260	3,000	341	1,000,000	384
95	76	280	162	850	265	3,500	346	10,000,000	384
100	80	290	165	900	269	4,000	351	500,000,000	384

The sample size of 310 was corroborated using the sample size calculation formula developed by Cochran (1977). According to Cochran (1977) $n_0 = [t^2 \times s^2] \div d^2 \rightarrow$ (1)

where n_0 = sample size.

t = t-value for a particular confidence level (confidence level usually used by researchers is 95%); s = estimate of standard deviation (calculated as s = number of points on the scale ÷ number of standard deviations) [e.g. if a researcher used a five-point scale and given that four standard deviations (two to each side of the mean) are there]; and d = acceptable margin of error [calculated using the formula (number of points on primary scale multiplied by an acceptable margin of error)].

Thus, for this research, the following values were used in determining the sample size.

t = 1.96 (for a confidence level of 95%)

s = 5 ÷ 4 = 1.25

d = 5 x 0.02 where 0.02 is the assumed margin of error (that is 2% margin of error) = 0.1

Thus, from equation (1)

$n_0 = [(1.96)^2\ (1.25)^2] \div (0.1)^2 = (3.84)\ (1.56) \div (0.01) = 5.99 \div (0.01) = 599.$

That is to say that if a margin of error is assumed to be 2%, then the sample required is 599. However, if the margin of error is assumed to be 3% then the sample size was found to be 266. While in this research the margin of error was assumed to be 3% and the sample size was calculated as 266, a correction was sought to be introduced as suggested by Cochran (1977). A correction factor is useful if the sample size calculated exceeds 5% of the total population. 5% of the total number of 15,000 healthcare professionals = 750. However, the sample size of 266 does not exceed 750. Therefore, there is no need for the correction factor to be calculated for the current research. The final estimated sample size for this research, therefore, is 266. A comparison of the sample sizes of 310 obtained using tables 4.9 and 266 obtained using the formula suggested by Cochran (1977) shows a difference. That is to say that the sample size obtained using the table developed by Krejecie and Morgan (1970) indicates that a maximum of 310 sample subjects are needed for distributing the research instrument and collecting data. On the other hand, a minimum of 266 sample subjects are needed if the formula developed by Cochran (1977) is applied. Taking into consideration this, in this research about 500 subjects were identified for distributing the research instrument for the collection of data. The online method was used to approach the participants identified for this research. As explained (in section 4.8.2) Google forms were used to post the instrument.

Many studies that are related to the medical field use surveys (Mondal et al., 2018) because surveys which are well-designed aid in getting data from a big sample in a short period (Jones et al., 2013). Online surveys are currently popular in medical fields (Mondal et al., 2018) due to the advancement of electronic mail, instant messages, or other online social platforms, for instance (WhatsApp) (Aziz et al., 2018). However, it must be noted that online surveys have a lower response rate than physical surveys (Sinclair et al., 2012) which implies that the researchers must access a larger number of participants to elicit the required responses.

Taking into consideration the above, in this research about 500 subjects were identified for distributing the research instrument for the collection of data. Literature shows that other researchers have also used similar sampling procedures and sizes. For instance, Lee and Lee (2020) studied factors affecting continuous intention to use healthcare wearables and used random sampling. Medical personnel and healthcare professionals on the administrative side were the target population. A total of 500 questionnaires each were sent to the medical personnel and general public, and a total of 354 (compromising of 289 medical professionals and 65 administrative staff working in the healthcare sector) valid responses were received by the researchers for analysis. Similarly, Pang et al. (2020) studied factors affecting the continued use intention of consumers using knowledge-sharing platforms. In their study, the authors used 512 valid responses from consumers who used knowledge sharing platforms which included the health sector. In another example Ahmad et al., (2020) who studied factors influencing elderly diabetic patients' continuance intention to use digital health wearables, used 223 valid responses received from elderly diabetic patients in Bangladesh chosen randomly. These examples of sample subjects used by researchers conducting similar research as that of this research confirm the validity of the sample size used in this research. Furthermore, the Online method was used to approach the participants identified for this research. As explained in section 4.8.2. Google forms was used to post the instrument.

Many studies that are related to the medical field use surveys (Mondal et al., 2018) because surveys which are well-designed aid in getting data from a big sample in a short period (Jones et al., 2013). Online surveys are currently popular in medical fields (Mondal et al., 2018) due to the advancement of electronic mail, instant messages, or other online social platforms, for instance (WhatsApp) (Aziz et al., 2018). However, it must be noted that online surveys have a lower response rate than physical surveys (Sinclair et al., 2012) which implies that the researchers must access a larger number of participants to elicit the required responses.

Google Forms has many advantages. It is a free web tool that enables users to create and distribute surveys and polls to authorised users with the support of Google Drive which is Google's cloud-based file storage system (Djenno et al., 2015). This technique is practically easy to adopt and environmentally friendly. In addition, the collected data can be exported to spreadsheets directly. Data collected can be viewed online or downloaded to spreadsheet software like Microsoft Excel for simple, quick, and easy data analysis (Rohmah et al., 2018). It must be noted here there using Google Forms is not the only way to disseminate the research instrument as literature shows that there are other ways to reach the sample subjects. These methods are tabulated in table 4-10 and a comparison of the benefits and drawbacks of different methods is provided in the same table (Aziz et al., 2018).

Table 4-10: List of methods of dissemination of research instrument, their benefits and drawbacks

Mechanism	Benefits	Drawbacks
Using email for online questionnaires circulation.	➢ **Low-cost** ➢ Fast response ➢ Larger geographic region ➢ No need to pay surveyors ➢ Maximum comfort ➢ low pressure, and privacy ➢ Paperless ➢ The result could be generated automatically in excel format.	➢ Low response rate ➢ Difficulty accessing personal email. ➢ Skipped response. ➢ Inactive/wrong email address ➢ Online questionnaire development requires a computer and graphical abilities.
Using Instant Messages such as (WhatsApp Application or any other messages facilities) for online questionnaires circulation.	➢ Cheap ➢ Higher return rate ➢ Larger geographic area ➢ No need to pay surveyors ➢ Quick response time ➢ Easy to follow up. ➢ Easy to review and communicate with the sample for any inconsistent or missing data. ➢ The respondent may answer during their leisure time. ➢ Increase comfort. ➢ reduce pressure. ➢ Paperless ➢ The final data will be displayed by auto-generated in excel format.	➢ The use of a personal phone for communication may threaten privacy. ➢ The domain of an online application may change over time. ➢ Issues with accessibility ➢ A smartphone with internet access is required for the target sample. ➢ The risk of an uncontrollable target sample. ➢ The transmit message may be replicated and spread like wildfire. ➢ It may be auto-generated in Excel format.
Face-to-face distribution of a paper-based questionnaire	➢ Concentrated attention on the target sample ➢ Quick response on the spot. Simple to examine and communicate with the sample for any inconsistencies or missing data. ➢ Waiting for the respondent to self-administer the questionnaire is time-consuming.	➢ Expensive ➢ Due to time and money constraints, researchers may choose to limit the smaller border distribution. ➢ Some people declined to react on the moment. ➢ Difficult to follow up. ➢ Possibility of hiring a surveyor to gather data. ➢ Face-to-face distribution tends to be dishonest. ➢ High paper use ➢ Manual data entry

4.10.3. Data collection

Identified participants were invited through an invite sent online by email or social media outlets. The Google Form link (https://docs.google.com/forms/d/e/1FAIpQLScc7Z2NbHAPmsqbWHvv5AEJBdHErM08fWrE3Zm1yt2c2T-YOA/viewform) was sent to those participants. Hundreds of responses were collected online from healthcare professionals working in 10 hospitals (2 public hospitals and 8 private healthcare centres and clinics) between August 27 and October 30, 2020. The URL was sent to over 500 sample subjects through e-mail, WhatsApp, and social media platforms. A total of 354 valid responses were finally received from the respondents. The data collected thus was then analysed as per the data analysis procedure delineated next.

4.11. Data analysis

SPSS software version 21 and AMOS software version 18 were used in data analysis. SPSS was used to conduct statistical analysis of descriptive statistics, missing data analysis, presence of outliers, checking normal data distribution and multicollinearity instances in the data. SPSS is a widely used software in statistical analysis by researchers (Francis et al., 2016; Janssens et al., 2008). AMOS (Analysis of Moments Structures) was used to conduct statistical analysis related to confirmatory factor analysis (CFA), model analysis (model estimation), model evaluation (model fit) and model path analyses (Abramson et al., 2005). It is widely used in structural equation modelling (Arbuckle, 2021). AMOS has the built-in feature of analysing both mathematically and pictorially and can test, modify and retest both specified models and alternate models. In addition, this software provides the facility to test the equivalence of groups or samples and test hypotheses. The benefits provided by AMOS enabled the researcher to apply it for statistical analysis in this research an argument supported by other researchers (Ullman, 2001; Arbuckle & Wothke, 1999).

4.11.1. Data preparation

The data analysis began with the coding of data using SPSS software. As Pallant (2020) says it is important and necessary to prepare a codebook so that information or data could be entered from the research instrument into SPSS. Coding involves coding the the variables, variable definition, labelling each one of the variables and assigning numbers to every one of the possible responses (Pallant, 2011). Appendix 6 provides the different variables used in the research instrument and their abbreviated form which were used in SPSS as codes for analysis.

Data edition was carried out and the completeness of the data was ascertained. SPSS provided the tools to accomplish this in terms of the frequency distribution command. The descriptive statistics facility in SPSS provided the support for the researcher to screen the data against each variable and ascertain whether responses coded as numbers were out of range. No errors were found as the data obtained through Google Forms posted online was transferred directly to a Microsoft Excel sheet by using the export facility provided in Google Forms. The data transferred to a Microsoft Excel sheet was further copied onto an SPSS file which was maintained throughout the study.

4.11.2. Descriptive analysis

Initial data analysis included the computing of descriptive statistics of the collected data including minimum, maximum, frequency, mean, standard deviation, skewness and kurtosis by using SPSS. Standard deviation provides information on the deviation of the distribution of the data from the normal while skewness and kurtosis enabled the researcher to test the normality of the data (Niyungeko, 2022). According to Pallant (2020), descriptive statistics provide several advantages which include a description of a sample's characteristics, examining the variables for any violation of assumptions that underly the statistical techniques and addressing a particular set of research objectives.
As far as the limits of standard deviation around the mean are concerned, there is no consensus amongst the researchers on the number of standard deviations that is acceptable around the mean. For instance, on a Likert scale of five points, the mean could be 3 with a maximum allowable standard deviation of ±2 while on a three-point Likert scale it could be ±1 standard deviation. However, researchers like Miller (1991) suggest a standard deviation of ±2 as acceptable around the mean. Considering the above arguments for this research standard deviation around the mean was fixed at ±2.

4.11.3. Normality of data

An important aspect of data analysis is the need to have normally distributed data. Skewness indicates the extent of the asymmetry of the distribution of data about the data of a variable present in a normal curve. A positive value of skewness indicates that the tail on the left side is the normal curve is shorter than the right while a negative value of skewness indicates that the right side is shorter than the left tail (Wulandari et al., 2021). Kurtosis indicates the extent to which the normal curve has peaked. For instance, where the normal curve is flat with heavy tails, kurtosis is positive and the data are distributed around the mean and extreme tails, while where the tail is light, kurtosis is negative and lower data points are distributed around the mean and the tails indicating a distribution of data around the mid ranges (Tamarin-Brodsky et al., 2022). As far as skewness and kurtosis values are concerned there is no consensus amongst the researchers on what is the acceptable value that indicates normality of data distribution. For instance, some (Ramos et al., 2018; Demir et al., 2016; Büyüköztürk et al., 2014; Huck, 2012) consider an absolute value of 1 as indicative of normal data while others (Şirin et al., 2018; Iyer et al., 2017; Perry et al., 2017; Kim, 2013; West et al., 1996) larger values of skewness and kurtosis indicate data normality. Thus, based on the discussions above and the recommendations of Lei and Lomax (2005) for this research a skewness limit of ±2 and a kurtosis limit of ±3 (moderate non-normality) were chosen to indicate the normality of the data. At this point, it was assumed that the data are normal and the same was tested in chapter 5).

4.11.4. Missing data, outliers and multicollinearity

Further to understanding the normality of the collected data, the next step carried out was checking for missing values. All the 354 valid responses received from the subjects did not have any missing values. The presence of outliers was checked using Mahalanobis Distance, facilitated by SPSS and the number of outliers found was negligible. The presence of outliers could cause concerns to statistical analysis and distort results (Hair et al., 2019). Another important parameter that was statistically checked was multicollinearity. According to Pallant (2020) when the dependent variables are highly correlated then it is said that multicollinearity is present. Hayduk (1987) suggests that correlational values of the dependent variables exceeding 0.8 could indicate the presence of multicollinearity. In such cases, Pallant (2020) argues that those pairs of dependent variables that have a very high correlation exceeding 0.8 should be combined to form a single variable. Thus, for this research 0.8 was used as the limit to check the presence of multicollinearity between variables. After discussing the details regarding the different aspects involved in data analysis the next section discusses the structural equation modelling that was used to analyse the research model (see figure 3.7).

4.11.5. Need for structural equation modelling

Once the data has been prepared, the next step taken was to analyse the research model using the prepared data and statistical techniques. The model analysis could be done using descriptive or correlational or multiple regression analysis or structural equation modelling (Hair et al., 2021). Amongst these methods, multivariate regression analysis generates a better picture of the model than descriptive and correlational analysis (Abramson et al., 2005). But structural equation modelling is argued to produce a much better picture of the model under testing and such a picture is enriched by it as it combines what is called factor analysis and multiple regression both of which are used to test the research model and hypotheses. Factor analysis is a step that enables the researcher to reduce a set of variables to a smaller set that represents the underlying factors and determines the variables that load on each factor (Abramson et al., 2005). Abramson et al. (2005) further argue that structural equation modelling goes beyond the power of both factor analysis and multiple regression. However structural equation modelling could be a challenge for statisticians as it requires substantive expertise (Bollen & Noble, 2011). Thus, to gain a greater understanding of structural equation modelling the following sections discuss and review structural equation modelling critically. It is important at this stage to note that structural equation modelling is associated with important terminologies that need to be understood if one has to apply it for data analysis and hypotheses testing. A list of these terminologies is provided in Appendix 10.

4.12. Structural equation modelling

Hair et al. (2021) argue that structural equation modelling is a method using which a researcher could simultaneously model and estimate complex relationships among multiple dependent and independent variables. While estimating relationships the method takes into account the measurement error in variables called observed variables. Observed variables also called manifest variables are those which are measured effectively, for instance, the score on the 5-point scale used in the research instrument. These observed variables are presented as squares or rectangles (Janssens et al., 2008). The concepts represented by elliptical representations are unobservable concepts that are under consideration in the research model in figure 3.7 and are measured indirectly by multiple observed indicators. The unobservable concepts are called latent variables (Janssens, 2008). The relationship between the observed and latent variables is estimated in structural equation modelling which accounts for measurement errors also in observed variables which leads to obtaining a more precise measurement of theoretical concepts being examined (Cole & Preacher, 2014).

Structural equation modelling facilitates the explanation of the variation in the dependent variables as a function of the independent variables and defines the direction of interaction between variables. In addition, structural equation modelling enables the simultaneous examination of multivariate regression equations which may include mediators and moderators (Byrne, 2001; Kline, 1998). It also provides facilities for the researchers to examine alternative model structures and relationships between constructs and variables (Byrne, 2001; Ullman, 2001; Kline, 1998). Furthermore, structural equation modelling enables the researchers to assess whether the same model could be applied across groups, and determine reliability and error terms (Byrne, 2001; Ullman, 2001).

The other features of a structural equation modelling include facilitating the researcher to make theoretical sense of the research model (Kline, 1998), examining the goodness fit of the model to the data (Kline, 1998), determining whether the model is parsimonious (Ullman, 2001; Arbuckle & Wothke,1999) and test whether the model is supported by theoretical underpinning or previous research (Abramson et al., 2005). Furthermore, structural equation modelling allows the researcher to examine the correspondence that could exist between the model covariance matrix and sample covariance matrix that is to say find how the two matrices are closer and estimate the research model, use its ability to estimate parameters through direct effect, means, intercepts, variances and covariances (Byrne, 2001) and fix parameters to pre-determined value or set them equal to other parameters as constraints or can be freely estimated (Joreskog, 1977). These features make the use of structural equation modelling better than the regression equation method.

The usual steps involved in structural equation modelling during model estimation are to specify and identify the model, select measures, collect data, clean and prepare data, analyse the model, evaluate the model and re-specify the model (Kline, 1998). Some of the limitations of the structural equation model include a possible error in judgement while determining cause and effect relationship between the independent and dependent variables as the analysis depends on correlational data and there is no transformation of correlational data to causal data (Cliff, 1983). In addition, structural equation modelling is criticised for the need to make assumptions at the beginning and those assumptions need to be tested before commencing the analysis failing which the results of the analysis may not be dependable (Abramson et al., 2005), for instance, the assumption that the data is normal. Despite criticisms yet structural equation modelling is widely used in empirical research as it is a powerful statistical tool that can produce dependable results.

As far as SEM is concerned, two methods are used by researchers namely covariance-based SEM (CBSEM), more specifically using the maximum likelihood (ML) estimation method and the Partial Least Squares (PLS) method. Using CBSEM it is possible to estimate parameters of the model for instance factor loadings and path values and minimize the difference that could exist between the sample covariances on the one hand and those determined by the theoretical model. The result is that the covariance matrix of the observed variable is reproduced during the process of parameter estimation (Chin & Newsted 1999) to test the overall goodness-of-fit measures. This further helps to check how well the hypothesized model fits the data (Barclay et al. 1995). CBSEM emphasizes testing a strong theory by checking the overall model fit. Accordingly, Gefen et al., (2000) argue that this method is best suited for confirmatory research.

In the case of the PLS method, the aim is to examine whether the dependent variables could be determined (both manifest and latent). Therefore, the goal is achieved by maximizing the explained variance (R^2 value) of the dependent variable. The parameters are estimated by minimizing the residual variances of the dependent variables. Thus, PLS is more suitable to be used in data analysis applications where the aim is predictive applications and theory building (exploratory analysis). It must be noted here that PLS can also be used in the confirmatory analysis (Barroso et al., 2010). It must be noted here that PLS can also be used in the confirmatory analysis.

As far as the limitations of the two methods are concerned it can be seen that the objective of CBSEM is more confirmative and less predictive while the objective of PLS is more predictive and less confirmative (Barroso et al., 2010). It must be noted here that PLS can also be used in the confirmatory analysis]. Next, PLS is used to derive hypotheses from a general theory which may not recognize all relevant variables and hence theory is less sound. However, in the case of the CBSEM, its use is primarily intended to confirm theories on which CBSEM is based, and not for deriving hypotheses (Barroso et al., 2010). Thus, the choice of either the CBSEM or PLS method by a researcher should be based on the aim the researcher wants to achieve namely whether it is the analysis that aims to determine or confirm a model. Taking into consideration the above discussion and taking into account the confirmatory nature of this research where the aim was to confirm theories, in this research CBSEM was adopted.

Iterative removal of observed variables is a general practice followed by researchers who adopt the SEM method to conduct data analysis (Arbuckle, 2021). While using SEM, confirmatory factor analysis is conducted to test construct reliability as well as the fitness of the model to data. During the process of data analysis squared multiple correlations (SMC) is used to test the construct reliability (Johari et al. 2011) [Wael thesis]. The minimum acceptable value recommended in the literature is found to be 0.3 (Holmes-Smith et al. 2006). On the other hand, it is also possible that an iterative process leading to the deletion of items could cause confirmation bias. Literature shows that confirmation bias is concerned with the tendency of people to search for information that backs up their beliefs and either ignores or distorts data that contradicts them (Myers & DeWall 2015: 357; Nickerson 1998. Mercier and Sperber (2017: 215) [Peters2020_Article_WhatIsTheFunctionOfConfirmatio] argue that confirmatory bias is generally considered to be an epistemically pernicious tendency. Mercier and Sperber further argue that bias acts as an obstacle while forming well-founded beliefs as well as decreases people's ability to correct those views that could have been formed by mistake. In addition, confirmation bias could lead researchers to reason on their own, thereby becoming overconfident (Mercier 2016: 110).

As far as structural equation modelling critics point out that one of the limitations is the confirmation bias indicating that certain relationships in a model are just accepted based on model fit or p-value, while those that do not satisfy the requirements are ignored (Kline, 2018). In fact, Kline (2018) claims that most researchers do not understand what p-value is. While the above information indicates the usefulness of confirmation bias, there is however serious criticism levelled against confirmatory bias. For instance, Hare (2006) argues that the concept of confirmation bias is being open-minded and is an attitude towards one's beliefs and such beliefs are independent of how certain one is. Hare (2006) further argues such an attitude does not clarify what it would mean to maintain such an attitude and how it can be linked and made compatible with firm belief. Considering the criticism levelled against confirmatory bias and the fact that reporting confirmatory bias is not a common practice amongst researchers in this research, confirmatory bias is not reported.

4.12.1. Structural equations

As far as the actual data analysis using structural equation modelling is concerned the following structural equations (multivariate regression equations) (Hair et al., 2021) representing the research model in figure 3.7 were tested.

$CI = k0 + \beta 1MOT + \beta 2TRN + e1$

$MOT = k1 + \beta 3RA + \beta 4CPX + \beta 5CMP + \beta 6TRI + \beta 7OBS + e2$

$TRN = k2 + \beta 8RA + \beta 9CPX + \beta 10CMP + e3$

where 'k' indicates a constant, 'β' indicates regression coefficient and 'e' indicates the error component. These multivariate simultaneous equations were tested using AMOS software version 18. Two steps were involved. They were confirmatory factor analysis and path analysis (Janssens et al., 2008).

4.12.2. Confirmatory Factor Analysis (CFA)

An important step in structural equation modelling is the confirmatory factor analysis that provides the basis to conduct hypotheses testing (Albright & Park, 2009). During this process, confirmatory factor analysis enables the researcher to arrive at the most optimum number of observed variables that are required to be used in the research model and tests the best fit of that model before the model is subjected to path analysis (Janssens et al., 2008). This in turn helps in refining the research instrument, assessing construct validity, method effects and factor invariance over cross-sectional and longitudinal time horizons, contexts like various groups (Brown, 2006), and reliability and validity of the research instrument scales (Carmines & Zeller, 1979). Important benefits offered by CFA include linking theory and observation, providing information on the best fit of the data to the model, enabling the researcher to identify potential weaknesses in the model, develop model conceptualisation, model identification, parameter estimation and model re-specification and ability to reject models or theories (Mueller & Hancock, 2008).

Limitations of confirmatory factor analysis include the possibility of losing some confirmatory characteristics of the analysis at the post hoc modification stage as some sort of exploratory factor analysis could creep in (Conway & Huffcutt, 2003). Additionally, the analysis could suffer due to a lack of basis for some assumptions made before beginning the analysis, for instance, the normality of the data which could create problems in model fitness (Hair et al., 2021; Raykov, 1998). Moreover, in many instances, the number of respondents in the research could be lower than the number of degrees which is not an acceptable condition when the Maximum Likelihood estimation method is used in the analysis (McCrae et al., 1996). The researcher has taken into account these limitations and ensured that those limitations do not cause concern by being cautious and following the steps prescribed in the literature.

4.12.3. Path analysis

Path analysis refers to the estimation procedure used to examine the relationships between latent variables. This leads to the estimation of the model in a way that the sample covariance matrix corresponds to the model covariance matrix as closely as possible (Janssens et al., 2008). Once the confirmatory factor analysis has provided the model for further estimation, path analysis is undertaken to determine the direction and nature of the final relationship between the variables for instance the independent and dependent variables. After discussing the structural equation modelling the next section reviews the method bias that could be introduced in the research when data is being collected using the same method (Jordan & Troth, 2020).

4.12.4. Common method bias and Unidimensionality

Citing Podsakoff and Organ (1986) in Jordan and Troth (2020) common method bias is said to creep into data analysis when the survey is used to collect all data on variables (e.g., relative advantage, motivation, continuous intention to use and artificial intelligence awareness) using the same method (example Likert scale) which could potentially lead to artificial inflation of relationships. Sources by which method bias is introduced include deploying only one type of item context, respondent, measurement context and item characteristics (Reio, 2010; Podsakoff et al., 2003). Especially when self-administered or self-reported surveys are used method bias could occur and needs to be tested (Podsakoff et al., 2003). According to Tehseen et al. (2017) there are a few tools used in the literature that have been used to determine method bias in the collected data which include Harman’s Single-Factor Test, Partial Correlation Procedures, Correlation Matrix Procedure and Measured Latent Marker Variable Approach (Tehseen et al., 2017; Podsakoff et al., 2003; Lindell & Whitney, 2001). Amongst these, in this research Harman’s Single-Factor Test was used. This test introduces all the observed variables into an exploratory factorial analysis and assesses the unrotated factor solution to get the number of components with Eigen values greater than one that explains the aggregate variance which it is assumed will happen if only method bias exists (Rodríguez-Ardur & Meseguer-Artola, 2020). The main advantage of using Harman’s Single-Factor Test is that is it simple to use and widely used in detecting common method bias (Kaltsonoudi et al., 2021). One of the major limitations of Harman’s Single-Factor Test is that it can only detect the presence of common method bias but cannot control it (Tehseen et al., 2017). After reviewing the common method bias the next section reviews the unidimensionality test used in this research to check in a set of variables only has one underlying dimension in common (Janssens et al., 2008). Unidimensionality is a routine test and is conducted using AMOS.

4.13. Ethical considerations

Novelskaitė and Pučėtaitė (2012) explain that ethics encompasses both the validity of conducted research and full respect for study participants and their communities and also the development of useful social policies and the effective dissemination and implementation of research results. Some (example Bell & Waters, 2014; O'Leary, 2014) emphasised that researchers should give simple checklists to create a questionnaire before conducting their questionnaire. Bell and Waters (2014) begin by reminding the researcher to receive consent from the participants and then focus on what the query is about and whether this is the right approach for collecting the expected information.

During the research journey, researchers may come upon ethical difficulties (Kjellström et al., 2010). To guarantee the rights and safety of participants, researchers use best practices, guidelines, and procedures (Osborne, 2017). A brief introductory letter was provided in the questionnaire to comply with Ryen's (2004) ethical research guidelines. Where the best practices enable researchers, regardless of their level of experience, to use a consistent set of ethical measures while maintaining high research standards.

This study required ethics approval because it obtained primary data from Bahraini healthcare professionals. Following the successful filing of the application for research ethics approval, according to Bradford University's Code of Research Ethics, ethical approval was received. The ultimate objective of receiving such ethics approval is to verify that the research is carried out professionally and ethically while protecting the participants' rights. In the application submitted for research ethics approval, the research questions, goals and objectives, as well as detailed information about research methods, target audiences, sampling techniques, data collection tools, questionnaire types, and survey objects are mentioned through the questionnaire, which was distributed for healthcare professionals in the Kingdom of Bahrain.

4.14. Chapter summary

This chapter provides a clear and distinct view of the research methodology developed and adopted for this research. In summary, it can be seen that this research has developed a research framework, which shows that a positivist research epistemology, objective ontology, deductive research approach and quantitative research methodology have been identified as part of the framework. In addition, the research strategy identified and used was the survey method. Cross-sectional research was conducted as it was found suitable to answer the research question and test the research model. Primary data was collected from healthcare professionals in Bahrain using a research instrument developed for use in the survey. A comprehensive data analysis procedure has been developed that shows that structural equation modelling is suitable for this research.

Thus, this chapter sets the basis for analysing the data collected for this research, which is discussed in the following chapter.

5. Chapter 5: Data Analysis

5.1. Introduction

In this chapter the collected data has been analysed and inferences derived. The chapter has tested the reliability and validity of data using tests described in the previous chapter. After testing the reliability and validity of the data, the data was analysed using structural equation modelling. SEM provided the basis to test the relationship between the constructs in the research model leading to the verification of the hypothesis. The chapter concludes by providing the results of the hypotheses testing, the inferences thereof and interpretations of the statistical analysis.

5.2. Descriptive

5.2.1. Descriptive Demographic

Initially the demographic characteristics of the respondents were analysed, and the results are tabulated in table 5-1 below.

Table 5-1: Demographic characteristics of respondents

Demographics Code	Gender		
	Frequency	%	Item
1	194	54.8	Male
2	144	40.7	Female
Total (n)	354		

In table 5-1 it can be seen that the difference between male and female healthcare professionals who participated in the research is about 14% indicating that both male and female healthcare professionals have evenly participated in the research.
Regarding age, it can be seen from table 5-2. that the number of participants in the age group of 26-33 years has participated the highest (35%) followed by the age group 34-41

(25.4%) indicating that the majority of participants (60.4%) are in the peak of their career and are perhaps the most likely candidates to continuously use IoMT.

Table 5-2: Age group of respondents.

#	Age		
	Frequency	%	Years-range
1.	30	8.5	18-25
2.	124	35.0	26-33
3.	90	25.4	34-41
4.	51	14.4	42-49
5.	59	16.7	>50
Total	354		

Similarly as far as the educational qualifications are concerned (table 5-3) the highest number of participants were those holding a professional certificate (34.2%) followed by bachelor's degree holders (32.5%) indicating that the likelihood of the continuous usage of IoMT is high because certificate holders are likely to be very familiar with the latest technologies and innovations that could be used in the healthcare support (Ali et al., 2021; Ahmad et al., 2018) followed by bachelor's degree holders who continuously undergo professional development to use the latest technology and innovations in providing the best healthcare support to patients.

Table 5-3: Educational qualifications of respondents

#	**Educational Qualification**		
	Frequency	**%**	**Qualification**
1.	6	1.7	High school graduate or equivalent
2.	191	54.0	Bachelor's degree
3.	74	20.9	Master's degree
4.	60	16.9	Professional certificate
5.	23	6.5	Doctorate
Total	354	100	

As far as the usage of IoMT is concerned it can be seen (table 5-4) that participants in the category "Using IoMT currently", "Aware of IoMT" and "Intend to use IoMT in future" constitute 65.8% of the total number of participants indicating that the majority of the participants are either using IoMT or aware of IoMT or intending to use IoMT in future. This is important as the responses have a direct utility to understand the continuous intention of the healthcare professionals to use IoMT, the variable that is a central part of this research. Although the percentage of participants who are "Not familiar with IoMT" stood at 34.2%, participating in this research is expected to have created awareness about IoMT amongst them and made them understand what IoMT is. There is every chance that in future those participants could intend to use IoMT.

Table 5-4: Usage of IoMT of respondents.

#	Usage of IoMT		
	Frequency	%	Item
1.	83	23.4	Using IoMT currently
2.	115	32.5	Aware of IoMT
3.	35	9.9	Intend to use IoMT in future
4.	121	34.2	Not familiar with IoMT
Total	354		

5.2.2. Descriptive (Constructs)

From chapter 4 (section 4.11) it can be seen that one of the important steps that need to be tested is the normal distribution of the data collected. This was tested using standard deviation, skewness and kurtosis. The SPSS report in table 5-5 shows that the standard deviation of all items was within the specified standard of ±1.5.

Table 5-5: SPSS report

Constructs	Items	Mean		Std. Deviation (≥±1.5)		Skewness (≥ ±2)		Kurtosis (≥ ±3)	
		Min.	Max.	Min.	Max.	Min.	Max.	Min.	Max.
Continuous Intention (CI)	CI1 -CI4	3.6864	3.8079	1.03326	1.17118	-1.077	-0.866	0.324	0.648
Relative Advantage (RA)	RA1-RA6	3.4463	3.6836	1.10854	1.14070	-0.818	-0.607	-0.195	0.127
Complexity (CPX)	CPX1 – CPX4	2.6271	2.9463	1.09694	1.31883	0.04	0.502	-1.118	-0.348
Compatibility (CMP)	CMP1-CMP4	2.9605	3.4576	1.01412	1.07849	-0.623	-0.379	-0.258	0.026
Trialability (TRI)	TRI1- TRI4	2.8559	3.0282	1.12368	1.1871	-0.227	0.051	-0.908	-0.685
Observability (OBS)	OBS1-OBS4	2.9209	3.1186	1.14775	1.16722	-0.279	-0.144	-0.955	-0.719
Training (TRN)	TRN1-TRN5	3.0282	3.3164	1.11609	1.16678	-0.508	-0.485	-0.64	-0.426
Awareness (AWS)	AWS1-AWS6	2.8983	3.3785	1.12774	1.18816	-0.533	0.055	-0.903	-0.49
Novelty Seeking (NS)	NS1- NS6	2.8729	3.4322	1.04991	1.15054	-0.647	0.037	-0.747	0.055
Motivation (MOT)	MOT1-MOT5	3.4633	3.5734	1.07511	1.10942	-0.672	-0.578	-0.145	0.092

The study of skewness and kurtosis helped verify the normality of data distribution (Hair et al., 2006). Skewness refers to the distribution's symmetry, whereas Kurtosis defined it as the degree or statistical measure of the peakedness of the distribution' (Mishra et al., 2019; Pallant, 2010). Normality tests can be performed using SPSS statistical tools (Mishra et al., 2019), therefore most statistical tools, give values of skewness and kurtosis and their usual errors (Kim, 2013). It can be seen that both skewness and kurtosis values were found to be within the acceptable limits of ±1.5 and ±3.0 respectively (section 4.11.3). The results show that the data collected was normally distributed. After testing the normality, the next section dwells on the construct reliability test.

5.3. Reliability

The reliability of the items used to measure the constructs have been tested using Cronbach's alpha. Table 5-6 provides the complete details of the reliability test.

Table 5-6: Reliability and Validity Assessment

Construct	Items	Cronbach's Alpha (≥0.7)	Inter-item correlation (≥0.3)		Total Item correlation (≥0.5)		Remarks
			MIN	MAX	MIN	MAX	
Continuous Intention (CI)**	CI1 – CI4	**0.919**	0.661	0.818	0.769	0.867	All items retained at this stage.
Relative Advantage (RA)*	RA1 – RA5	**0.951**	0.633	0.842	0.802	0.888	All items retained at this stage.
Complexity* (CPX)	CPX1 To CPX 4	**0.803**	0.363	0.694	0.483	0.709	All items retained at this stage.
Compatibility* (CMP)	CMP1 To CMP 4	**0.847**	0.479	0.654	0.631	0.771	All items retained at this stage.
Trialability (TRI)*	TRI1 To TRI4	**0.856**	0.567	0.704	0.674	0.725	All items retained at this stage.
Observability (OBS)*	OBS1 To OBS4	**0.807**	0.434	0.578	0.592	0.653	All items retained at this stage.
Training (TRN)**	TRN1 -TRN5	**0.940**	0.650	0.813	0.786	0.863	All items retained at this stage.
Awareness (AWS)*	AWS1 – AWS6	**0.922**	0.541	0.902	0.654	0.869	All items retained at this stage.
Novelty Seeking (NS)*	NS1 To NS4 and NS6	**0.827**	0.207	0.880	0.327	0.746	Item NS5 deleted to improve Cronbach's alpha as it was causing concern
Motivation (MOT)**	MOT1 – MOT 5	**0.915**	0.433	0.850	0.657	0.896	All items retained at this stage.
*Indicates exogenous constructs							
**indicates endogenous constructs							

According to the literature the acceptable level of Cronbach's Alpha is greater than 0.7 (Bahuri et al., 2021; Adjisasmita et al. 2020; Hair et al., 2006). Table 5-6 shows that all constructs are satisfying this criterion indicating that the data collected is reliable. In addition, two more tests were conducted to check the reliability aspect namely inter-item correlation and item to total correlation also termed internal consistency measures. Literature shows that valid inter-item correlation for all constructs should be greater than 0.3 (Rafati et al., 2021; Sarhan, 2020). From table 5-6 it was found that all values of inter-item correlation were greater than 0.3. Similarly, literature shows that the acceptable item to total correlation should be greater than 0.5 (Edirisinghe et al., 2021; Hair et al., 2019). From table 5-6 it can be seen that item to total correlation for all constructs was found to be above 0.5. Thus, it was concluded that the reliability of the items used to measure the constructs as well as the data collected is reliable. SPSS software, version 21 was used to test the reliability of the items. Further, construct reliability was measured under the section CFA to check whether the covariance values between the latent variables and manifest variables satisfy minimum conditions and is reliable and valid as suggested by Holmes-Smith et al. (2006). After determining the reliability measure, the next measure tested was validity aspect.

5.4. Validity

According to literature different validity tests are usually conducted to ascertain the data validity namely content validity, criterion validity, convergent validity, discriminant validity and construct validity (section 4.9.3) (Creswell & Creswell, 2018). Content validity was ascertained by obtaining feedback from an academic, a researcher, a consultant and a participant on the contents of the research instrument, the layout of the instrument, the format and instructions given to respond to the items. Some minor modifications were made to the wordings based on the feedback received from those consulted and the instrument was launched. Criterion validity was measured using inter-item correlation and as mentioned above acceptable values were set at ≥0.3 for any construct. It can be seen from table 5-6 that all inter-item correlations were found to be > 0.3. Convergent validity was tested using the item-total correlation. As explained above, an acceptable level of item-total correlation was set at ≥0.5. From table 5-6, it can be seen that for all constructs, the item-total correlation was found to exceed 0.5 indicating that convergent validity was established. Construct validity is a measure of convergent validity (Creswell & Creswell, 2018), It can be seen from the statements above that convergent validity has been already found have been achieved. Except for content validity, all other validity tests were conducted using SPSS software, version 21. Thus, at this stage, it can be concluded that validity of data has been achieved except for discriminant validity which will be discussed later in this chapter as it involves using AMOS software as part of structural equation modelling which is discussed next.

5.5. Structural equation modelling

According to the literature structural equation modelling (SEM) is used to estimate a group of regression equations simultaneously (Hernández-Sanjaime et al., 2021; Janssens et al., 2008) and generate a tested model that would enable the determination of the continuous intention of the users of IoMT in the healthcare sector. SEM enabled the researcher to test the base model and arrive at a redefined model. The theoretical model given in figure 3.7 is represented by the set of regression equations given in section 4.12.1. These equations were analysed using SEM. The main purpose of using structural equation modelling is to analyse whether the set of variables used in the theoretical model could be shrunk to a smaller set of underlying factors and extract the variables that load on each of those underlying factors (Abramson et al., 2005). Furthermore, SEM enabled the researcher to explain changes that take place with regard to the dependent variable (continuous intention to use IoMT) due to changes occurring in the independent variables (DoI factors) like the multiple regression analysis. By this the researcher was able to test alternative model structures and relationships that could exist between the exogenous and endogenous variables, an argument supported by the extant literature (Byrne, 2001; Kline, 1998; Ullman, 2001). Moving on further, the following sections have implemented SEM in two steps namely the CFA (measurement model) and path analysis (structural equation model) (Janssens et al., 2008). Each one of these steps is discussed next.

5.6. Confirmatory Factor Analysis

Confirmatory factor analysis is considered to be a powerful tool in statistical data analysis to examine the relationships between latent variables (Prudon, 2015) e.g., relative advantage, motivation and continuous intention to use (Jackson et al., 2009). CFA provides a method by which it was possible for the researcher to analyse the research model in the process of answering the research questions. The use of CFA has been found in research concerning the diffusion of IoT related to healthcare (e.g., Ahmad et al., 2020; Nikou, 2018). The basic model used to conduct CFA using AMOS is provided in figure 5.1.

In order to conduct CFA, the confirmatory model was drawn using AMOS. The initial confirmatory model is provided in figure 5.1.

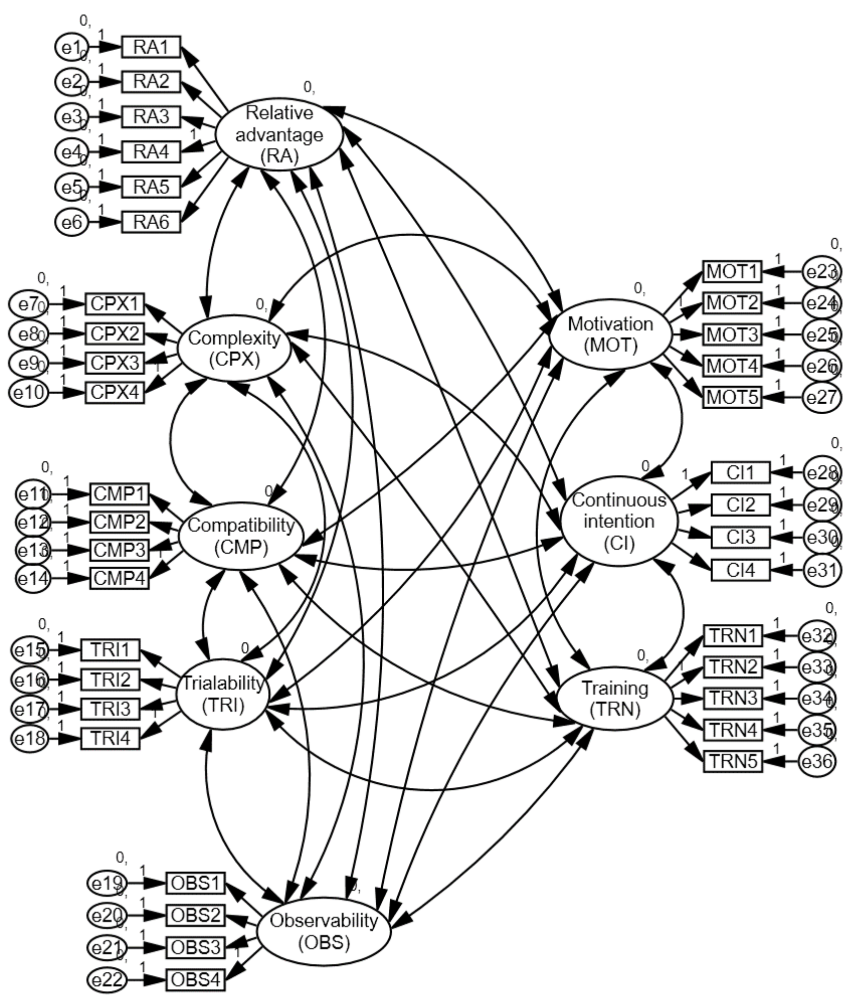


Figure 5.1: Initial covariance model

The CFA model depicted in figure 5.1 has eight constructs identified as exogenous and endogenous variables (table 5-7) and is measured by a total of 36 items.

Table 5-7: List of exogenous and endogenous variables.

Constructs	Code	Items	Number of items	Definition
Continuous Intention*	CI	CI1 -CI4	4	Continuous intention to use IoMT (User behavioural attribute)
Relative Advantage**	RA	RA1-RA6	6	Relative advantage of IoMT (Diffusion of innovation factor)
Complexity**	CPX	CPX1 – CPX4	4	Complexity of IoMT (Diffusion of innovation factor)
Compatibility**	CMP	CMP1-CMP4	4	Compatibility of IoMT (Diffusion of innovation factor)
Trialability**	TRI	TRI1- TRI4	4	Trialability of IoMT (Diffusion of innovation factor)
Observability**	OBS	OBS1-OBS4	4	Observability of IoMT (Diffusion of innovation factor)
Training*	TRN	TRN1- TRN5	5	Training to use IoMT (User behavioural attribute)
Motivation*	MOT	MOT1-MOT5	5	Motivation to use IoMT (User behavioural attribute)
Note: ** Indicates exogenous variables; *Indicates endogenous variable.				

One of the important uses of CFA is that it can be applied to conduct the construct reliability and validity. Outcomes of testing construct reliability and validity informed the researcher about the covariance that exists between the latent variables and manifest variables and check whether the covariance values satisfy minimum conditions and are reliable and valid (Holmes-Smith et al., 2006). The latent variables in the research were: Continuous Intention (CI), Relative Advantage (RA), Complexity (CPX), Compatibility (CMP), Trialability (TRI), Observability (OBS), Training (TRN) and Motivation (MOT). Each of these latent variables accounts for a certain number of observed variables used in measuring the latent variables and are provided in tables 5.8 and 5.9.

Table 5-8: List of latent variables accounting for observed variables

Observed variables	Latent Constructs
CPX4	Complexity
CPX3	Complexity
CPX2	Complexity
CPX1	Complexity
RA4	Relative advantage
RA3	Relative advantage
RA2	Relative advantage
RA1	Relative advantage
RA5	Relative advantage
RA6	Relative advantage
CMP4	Compatibility
CMP3	Compatibility
CMP2	Compatibility
CMP1	Compatibility
TRI4	Trialability
TRI3	Trialability
TRI2	Trialability
TRI1	Trialability
MOT2	Motivation
MOT3	Motivation
MOT4	Motivation
MOT5	Motivation
MOT1	Motivation
TRN2	Training
TRN3	Training
TRN4	Training
TRN5	Training
TRN1	Training
OBS4	Observability
OBS3	Observability
OBS2	Observability
OBS1	Observability
CI1	Continuous intention
CI2	Continuous intention
CI3	Continuous intention
CI4	Continuous intention

From table 5-8 it can be seen that there are 14 observed variables supporting three endogenous variables and 22 observed variables supporting five exogenous variables. It must be noted here that the initial research model provided in figure 5.1 does not include the two moderating variables. As the next step construct reliability was checked. Construct reliability was already checked using inter-item and item to total correlation earlier. However, researchers suggest that it is useful to test the construct reliability while conducting CFA using squared multiple correlations (SMC) between items as well as constructs. SMC is the square of the standardised loading of the observed variable on the latent construct (Johari et al., 2011). Reference values recommended in the literature are>0.3 (Holmes-Smith et al., 2006; Hailu et al., 2016; Kin, 2011). Table 5-9 provides the SMC between the observed variables in the model. From the table, it can be seen that SMC values were greater than 0.3 in all cases.

Table 5-9: Squared Multiple Correlations: (Group number 1 - Default model)

	Estimate
CI4	.819
CI3	.688
CI2	.831
CI1	.634
OBS1	.537
OBS2	.417
OBS4	.575
TRN1	.688
TRN5	.804
TRN4	.785
TRN3	.740
TRN2	.779
MOT1	.595
MOT5	.739
MOT4	.888
MOT3	.804
TRI1	.748
TRI2	.662
CMP2	.628
CMP3	.688
CMP4	.535
RA6	.704
RA5	.759
RA1	.703
RA2	.825
RA3	.774
RA4	.835
CPX3	.827
CPX4	.583

As far as validity is concerned, it can be seen that content, convergent, concurrent and construct validity have been already established in section 5.4, here the discriminant validity of the data is tested which was not tested earlier. Discriminant validity was tested using CFA and comprises four steps namely testing correlation amongst the latent variables, the residual and standard residual covariance between items, the verification of whether the covariance model fits the data and average variance extracted (AVE) (Fernandez & Moldogaziev, 2011; Shim & Eom, 2008; Janssens et al., 2008; Holmes-Smith et al., 2006; Joreskog & Sorbom, 1984). These tests were conducted using AMOS except for the average variance extracted test.

5.7. Sample correlation

Sample correlation reported by AMOS is provided in Appendix 11 at the observed variable level (Holmes-Smith et al., 2006; Gujarati, & Porter, 2012) mentioned that the correlation between two variables should not exceed 0.8. Higher than this could lead to multicollinearity problems (Amelia et al., 2019). There were 3 pairs of variables that had correlation problems exceeding 0.8. At this point, the pairs contributing to the problem in correlation were still retained and were observed for their performance during the investigation of residual and standard residual covariance.

5.8. Residual covariance and standard residual covariance

Literature (Joreskog & Sorbom, 1984) shows that residual and standard residual covariance are measures that are tested between any pair of items in a model and provide an idea of the sharing of variance between that pair of items in the model. Residual covariance between a pair of any two items is defined as (value of model-implied covariance matrix – the value of residual covariance matrix) (Bedeian, 1997). Standardised residual covariance between any two items is defined as (residual covariance/estimated standard error) (Joreskog and Sorbom, 1984). Bedeian (1997) suggests that the acceptable value of residual covariance values should lie between -0.1 and +0.1. Similarly, the acceptable values of standard residual covariance between any two items recommended in the literature are 2 (Wong & Dean, 2005) although a more appropriate value of 2.58 has been suggested by Abderrahman et al. (2012). Any value of standard residual covariance and residual covariance falling outside these reference values will be investigated further and the item or items contributing to this will be deleted from the model. Accordingly, AMOS was used to test the residual and standard residual covariance and the following items were deleted from the model namely CMP1, CPX1, CPX2, MOT2, OBS3, TRI3 and TRI4. The resulting items retained at this stage are given in table 5-10.

Table 5-10: List of retained items measuring latent constructs.

Constructs	**Retained items measuring the constructs**
CI	CI, CI2, CI3 & CI4
OBS	OBS 1, OBS2 and OBS4
TRN	TRN1, TRN2, TRN3, TRN4 & TRN5
MOT	MOT1, MOT3 and MOT4
TRI	TRI1, TRI2
CMP	CMP2, CMP3 and CMP4
CPX	CPX3 & CPX4
RA	RA1, RA2, RA3, RA4, RA5 and RA6

Finally, the last step in the CFA stage namely testing the fitness of the model to the data tested was conducted which is reported next.

5.9. Fitness test of the covariance model

Literature shows that it is important to fit the CFA model to data and report the fitness index (Li et al., 2021). Further Schermelleh-Engel et al. (2003) define model fitness measures the degree to which a CFA model fits the data collected and suggest that evaluating the model fit is recommended before specifying the final model. Some of the widely used fitness measures found in the literature include Goodness Fit Index (GFI), Comparative Fit Index (CFI), Normed Fit Index (NFI), Incremental Fit Index (IFI), Tucker–Lewis Index (TLI), Root Mean Residual (RMR) and Root Mean Square Error Approximation (RMSEA). Some other measures used include Chi-square (χ2) specified at a certain Degree of Freedom (DF) and p-value (> 0.05 required to reject the null-hypotheses) and CMIN/DF ratio (χ2) measurements (Schermelleh - Engel et al., 2003). Examples of different fitness indices are provided in table 5-11 with the widely accepted values of fitness indices by researchers.

Table 5-11: Widely reported fitness test statistics used to evaluate Model Fit (Schreiber et al. 2006; Byrne, 2001; Arbuckle & Wothke, 1999; Kline, 1999).

Fitness test statistics	**Abbreviation**	**Critical value**	**Meaning**
Goodness or fit index	GFI	0.9 < GFI <1	Good fit to the justified model
Normed fit index	NFI	0.9 <NFI <1.0	Percent improvement over null model
Tucker-Lewis index	TLI	0.9 <TLI <1.0	Percent improvement over null model
Comparative fit index	CFI	0.9 <CFI <1.0	Percent improvement over null model
Increment fit index	IFI	0.9 <IFI <1.0	Percent improvement over null model
Chi-squared goodness of fit test	CMIN ($\lambda^{2)}$	Chi-squared = n.s.	Good fit to the justified model

Normal Chi-squared test	CMIN/df	(Chi-squad/df) ≤ 3	Good fit to the justified model
Root mean square error or approximation	RMSEA	0 < RMSEA <0.08	Good model fit
Root mean square residual	RMR	Smaller the better	0 indicates perfect fit

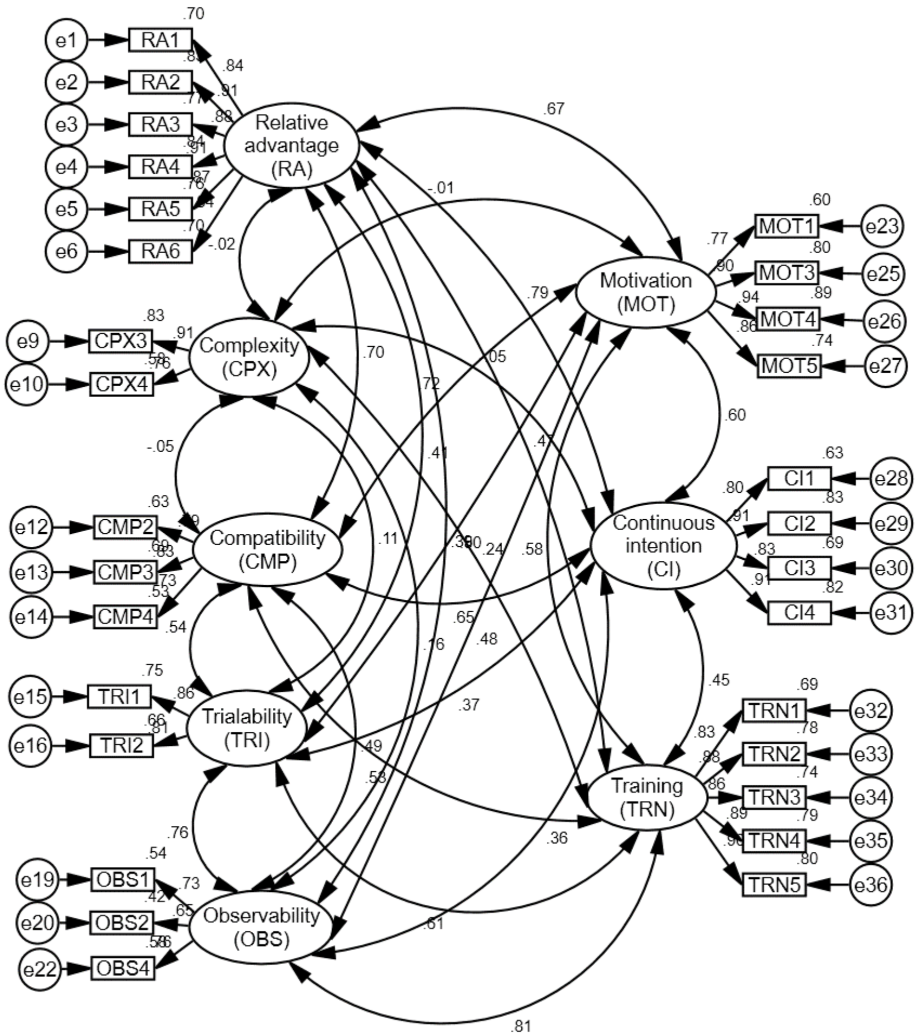


Figure 5.2: Final covariance tested model.

While there is no unique set of fitness indices tests that has been prescribed, it is found in the literature that researchers report more than one index usually. Accordingly, in this research IFI, CFI and RMSEA are reported. Where additional fitness measures are satisfactory, those fitness measures are also reported. According to the literature accepted value of fitness measures for IFI and CFI should be greater than 0.9 while for RMSEA it is found to be ≤ 0.08 (Kamaruddin and Matore, 2021). The values recorded by AMOS in this research at the CFA stage concerning the fitness indices were IFI = 0.928, CFI=0.928 and RMSEA = 0.072. Thus, it was concluded that the CFA model was fit to data and stands the scrutiny of the discriminant validity. At this stage, it can be seen that the optimum set of observed and latent variables has been arrived at for the research model which was further subjected to path analysis as the second part of the SEM. The resulting model that was tested using SEM is provided in figure 5.2.

There are many stages in SEM analysis, such as model specification, model estimation, model evaluation, model modification and model identifications (Owolabi et al., 2020; Lei & Wu, 2007). However, there are essentially two steps that are involved in testing the covariance tested model namely model analysis (also called model estimation) and model evaluation (also called model fit) (Abramson et al., 2005). Even before SEM is used to analyse the model in figure 5.2 it is necessary to specify the model that will be subjected to SEM. The initially specified full structural model is provided in figure 5.3. The next step taken was model analysis. According to Abramson et al. (2005), structural models highlight the relationships between the hypothesised latent variables, while measurement models highlight relationships between the manifest variables (observed variables) and the latent variables only. Full structural models combine both measurement and structural models (Ullman & Bentler, 2013; Ullman, 2001; Byrne, 2001; Arbuckle & Wothke, 1999; Joreskog, 1977; 1993).

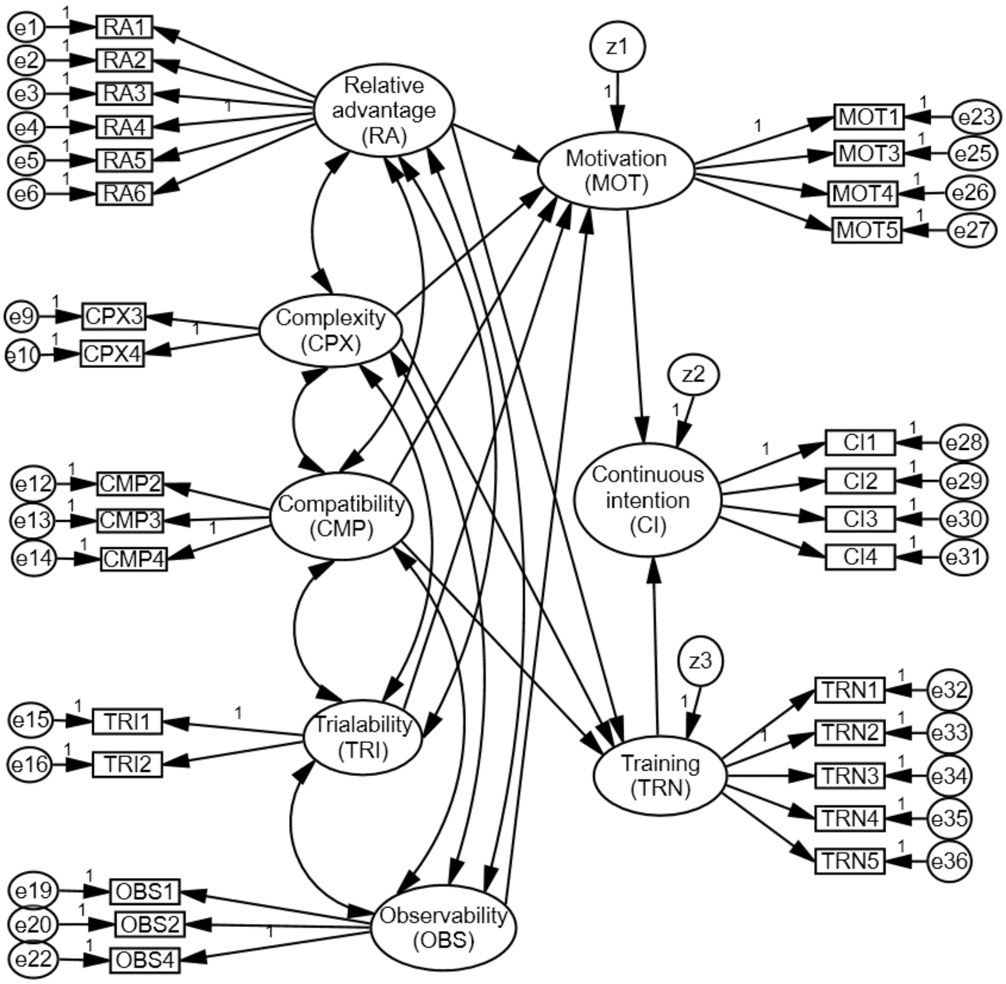


Figure 5.3: Initially specified structural model

Figure 5.3 is a combination of measurement and structural equation models. This is presented in figure 5.4.

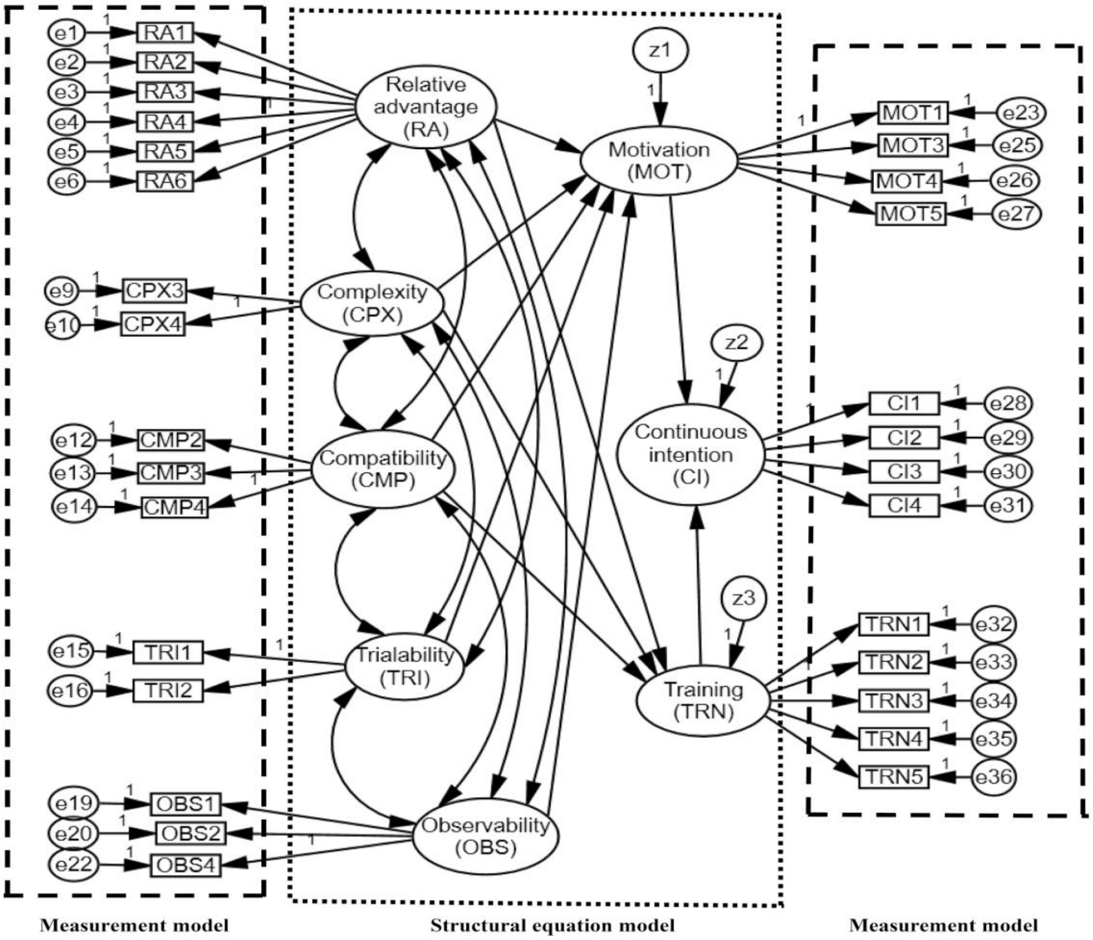


Figure 5.4: Representation of measurement and structural models

5.10. Model analysis (model estimation)

Model analysis or estimation is a process by which it is possible to test whether the research model fits the data or not. One of the methods commonly used in SEM, in estimating a research model is the maximum likelihood (ML) method (Kline, 1998). According to Owolabi et al. (2020) that ML is the most preferable and recommended strategy, because it is based on the assumption of normalcy. The steps involved are testing the discriminant validity using average variance extracted (AVE) method, testing the internal consistency of the constructs using composite reliability (CR), SMC and theoretical identification of the model. This, however, involves the testing of the model recursiveness, testing the multicollinearity of the observed variables and whether the number of parameters identified in the model is more than required or adequate or less) (Abramson et al., 2005). Outcome of each one of the above tests is analysed next.

5.10.1. Average variance extracted (AVE) and Internal consistency of latent constructs of the measurement model

Literature shows that average variance extracted is measured using the formula

Variance extracted = [∑(standardised loadings)^2/(∑(standardised loadings)^2 + ∑measurement errors)] where:

- Standardised loadings indicate the standard regression weights explained by each item on a latent construct those items are measuring; the square of it indicates the squared multiple correlations. For example, from table 5-12, it can be seen that for the construct relative advantage, the standardised loading for the item RA1 is 0.832. The squared multiple correlation is (0.832) = 0.692. Squared multiple correlations for other items are calculated in a similar way (Janssens et al., 2008). Standardised loadings for all items are provided in table 5-12.
- Measurement errors are calculated as (1- squared multiple correlations) (Janssens et al., 2008). From the previous bullet point, it can be seen that for RA1 measurement error is (1-0.692) = 0.308. Measurement errors for other items are calculated in a similar manner.

Standardised Regression Weights: (Group number 1 - Default model)

Table 5-12: AMOS report indicating standardised loading of each item on the corresponding latent construct generated by AMOS for the structural model in figure 5.3.

Items		Construct	Estimate
RA4	<---	Relative_advantage_(RA)	.914
RA3	<---	Relative_advantage_(RA)	.882
RA2	<---	Relative_advantage_(RA)	.907
RA1	<---	Relative_advantage_(RA)	.832
RA5	<---	Relative_advantage_(RA)	.875
RA6	<---	Relative_advantage_(RA)	.842
CMP3	<---	Compatibility_(CMP)	.807
MOT3	<---	Motivation_(MOT)	.893
MOT1	<---	Motivation_(MOT)	.775
TRN2	<---	Training_(TRN)	.876
TRN3	<---	Training_(TRN)	.866
TRN4	<---	Training_(TRN)	.891
TRN5	<---	Training_(TRN)	.902
TRN1	<---	Training_(TRN)	.815
OBS4	<---	Observability_(OBS)	.720
OBS1	<---	Observability_(OBS)	.757

Items		Construct	Estimate
CI1	<---	Continuous_intention_(CI)	.803
CI2	<---	Continuous_intention_(CI)	.917
CI3	<---	Continuous_intention_(CI)	.824
CI4	<---	Continuous_intention_(CI)	.896
CMP2	<---	Compatibility_(CMP)	.749
CMP4	<---	Compatibility_(CMP)	.704
TRI2	<---	Trialability_(TRI)	.818
TRI1	<---	Trialability_(TRI)	.861
CPX3	<---	Complexity_(CPX)	.898
CPX4	<---	Complexity_(CPX)	.765
MOT5	<---	Motivation_(MOT)	.861
MOT4	<---	Motivation_(MOT)	.936
OBS2	<---	Observability_(OBS)	.670

The average variance calculated is provided in table 5-13. According to the literature average variance extracted should be above 0.5 (Hair et al., 2017). The tabulations of average variance extracted shows that for all variables the AVE is greater than 0.5 as indicated by the values indicated in bold digits.

Table 5-13: Average variance extracted

	Relative advantage (RA)	Complexity (CPX)	Compatibility (CMP)	Trialability (TRI)	Observability (OBS)
Relative advantage_(RA)	**0.767**				
Complexity (CPX)		**0.696**			
Compatibility (CMP)			**0.569**		
Trialability_(TRI)				**0.705**	
Observability_(OBS)					**0.513**

Other cells in table 5-13 above are filled up as follows using the following table 5-14 generated by AMOS.

Correlations: (Group number 1 - Default model)

Table 5-14: Correlation amongst the latent constructs found in figure 5.3

			Estimate
Observability_(OBS)	<-->	Trialability_(TRI)	.764
Relative_advantage_(RA)	<-->	Complexity_(CPX)	-.022
Compatibility_(CMP)	<-->	Complexity_(CPX)	-.064
Compatibility_(CMP)	<-->	Trialability_(TRI)	.608
Relative_advantage_(RA)	<-->	Compatibility_(CMP)	.731
Complexity_(CPX)	<-->	Trialability_(TRI)	.130
Compatibility_(CMP)	<-->	Observability_(OBS)	.600
Observability_(OBS)	<-->	Complexity_(CPX)	.201
Relative_advantage_(RA)	<-->	Trialability_(TRI)	.406
Relative_advantage_(RA)	<-->	Observability_(OBS)	.382

RA-RA = AVE = 0.767

RA-CPX = $(-0.022)^2 = 0.00048 \approx 0.0005$

RA-CMP = $(0.731)^2 = 0.534$

RA-TRI = $(0.406)^2 = 0.165$

RA-OBS = $(0.382)^2 = 0.146$

These values are reflected in the first column in table 5-15.

Table 5-15: Discriminant validity

	Relative advantage (RA)	Complexity (CPX)	Compatibility (CMP)	Trialability (TRI)	Observability (OBS)
Relative advantage_(RA)	**0.767**				
Complexity (CPX)	0.0005	**0.696**			
Compatibility (CMP)	0.534	0.0041	**0.569**		
Trialability_(TRI)	0.165	0.0169	0.37	**0.705**	
Observability_(OBS)	0.146	0.04	0.36	0.584	**0.513**

Other values in table 5-15 were calculated similarly. It can be seen that none of the relationships in the matrix exceeds the AVE of a construct except for the construct observability where the squared multiple correlations for the relationship TRI-OBS (0.584) exceeds the AVE of OBS which is 0.513. This aspect was under observation and was reviewed at the time of testing the composite reliability, which is the internal consistency of the data.

As far as internal consistency of the latent construct items were concerned composite reliability was used as the measure and acceptable values ranged between 0.6 and 0.7 for exploratory research (Hair et al., 2017). The formula used for calculating the composite reliability is:

Composite reliability = [∑(standardised loadings)^2/(∑(standardised loadings)^2 + ∑measurement errors)] where:

- Standardised loadings: It is the figure generated by AMOS for an item concerning a particular latent construct (standardised regression weights given in table 5-12). For instance, for RA the standardised loadings are given in table 5-16.

Table 5-16: Standardised regression weights for the items measuring RA extracted from table 5-12.

Items		Construct	Estimate (standardised loadings)	Squared multiple correlation (SMC)	Measurement error (1-SMC)
RA4	<---	Relative_advantage_(RA)	0.914	0.835396	0.164604
RA3	<---	Relative_advantage_(RA)	0.882	0.777924	0.222076
RA2	<---	Relative_advantage_(RA)	0.907	0.822649	0.177351
RA1	<---	Relative_advantage_(RA)	0.832	0.692224	0.307776
RA5	<---	Relative_advantage_(RA)	0.875	0.765625	0.234375
RA6	<---	Relative_advantage_(RA)	0.842	0.708964	0.291036
		∑(standardised loadings)	5.252		1.397

[∑(standardised loadings)^2] = $(5.252)^2$ = 27.583504 (from table 5-16)

- Measurement error is the difference resulting while subtracting the square of the standardised loadings (that is the squared multiple correlations (SMC) from 1 for each one of the items measuring RA. That is (1-SMC). The tabulated results of (1-SMC) for all the items namely RA1 to RA6 are provided in table 5-16.

  Thus ∑Measurement error = ∑(1-SMC) = 1.397

Composite reliability of RA

= [∑(standardised loadings)^2]/ [(∑(standardised loadings)^2) + ∑Measurement error]

= (27.58)/(27.58+1.397) = 0.952

Composite reliability for other constructs is calculated in a similar manner and are tabulated in table 5-17.

Table 5-17: Composite reliability of exogenous variables in figure 5.3

RA	0.952
CPX	0.82
CMP	0.798
TRI	0.83
OBS	0.76
MOT	0.92
TRN	0.94
CI	0.92

The results of the composite reliability calculated and provided in table 5-17 above show that all the values of composite reliability pertaining to the exogenous constructs are above 0.7 indicating that the internal consistency measures of the data for all the constructs are reliable. At this point, it can be seen that although the relationship TRI-OBS showed an anomaly with regard to the AVE value of OBS, the composite reliability value for OBS is showing a good strength at 0.76 confirming that the data is reliable and valid. This inference is arrived at because amongst the four measures identified for computing the discriminant validity in this research three measures namely correlation amongst the latent variables, the residual and standard residual covariance between items and the verification of whether the covariance model fits the data have been found to be satisfying the requirements set in this research. As far as average variance extracted is concerned while the AVE values for the constructs have been found to be higher than 0.5, which indicates that discriminant validity is established. One relationship TRI-OBS was found to have an SMC higher than OBS-OBS. Considering these aspects, it was concluded that discriminant validity of the data has been established for use in examining the structural model.

5.11. Squared multiple correlations (SMC)

Squared multiple correlations is similar to the R^2 statistic of a variable measured in the multivariate regression. SMC provides the basis for testing fitness. SMC is provided in table 5-18. As explained earlier acceptable value of SMC should be greater than 0.3 (Hailu et al., 2016; Kin, 2011). The readings in table 5-18 clearly show that SMC values are greater than 0.3.

Table 5-18: Squared Multiple Correlations: (Group number 1 - Default model)

	Estimate
Training to_use IoMT	.574
Motivation to_use IoMT	.722
Continuous_intention to_use IoMT	.430
CI4	.802
CI3	.682
CI2	.844
CI1	.647
OBS1	.685
OBS2	.415
TRN5	.879
TRN4	.752
MOT1	.579
MOT5	.783
MOT4	.842
TRI1	.767
TRI2	.646
CMP2	.429
CMP4	.420
RA6	.725
RA5	.806
RA3	.755
CPX3	.980
CPX4	.491

5.12. Model identification

Theoretically identified models are those which indicate that a unique numerical solution is possible and there is an identified value for every one of its parameters (Ullman & Bentler, 2012; Bollen & Noble, 2011; Abramson et al., 2005). Theoretically identified models could be an under-identified model (independence model reported by AMOS where the number of parameters is higher than the number of data points), an over-identified model (default model, where the number of parameters is lower than the number of data points) and just-identified model (saturated model, where the number of parameters is equal to the number of data points) (Mutuli & Bukhala, 2020; Ullman & Bentler, 2012; Kline, 1998). The default model is the structural model of the researcher (Mutuli & Bukhala, 2020) in which the number of parameters is equal to the sum of the number of regression coefficients, variance and covariance (Ullman & Bentler, 2012; Ullman, 2006). According to the literature, three tests are conducted to identify a model namely that the number of parameters is less than the number of data points, test whether the model is recursive, and check that multicollinearity is absent (Abramson et al., 2005). Furthermore, Ullman and Bentler (2012) explain that in order to proceed with the analysis of the model, it is a necessary condition that the model needs to be overidentified and argue that the hypotheses about the adequacy of a model cannot be tested if the model is just identified. In under-identified models, it is not possible to estimate the parameters meaning model analysis will suffer (Ullman, 2006). AMOS provides the report (table 5-19) on the number of parameters and data points available on the model.

Table 5-19: AMOS report on the number of parameters and data points

Notes for Model (Default model)	
Computation of degrees of freedom (Default model)	
Number of distinct sample moments:	435
Number of distinct parameters to be estimated:	78
Degrees of freedom (435 - 78)	357

From table 5-19 it can be seen that the model is identified as the number of parameters (78) are much less than the number of data points (sample moments) which is 435. The number of data points can be calculated and verified using the formula suggested by Ullman and Bentler (2012), which is:

Number of data points = p(p-1)/2

where p is the number of measured variables. From figure 5.4 it can be seen that the number of measured variables (observed variables) = 29. Thus, the number of data points = [p(p+1)/2] = [29 (29+1)/2] = 435. This figure is identical to the one produced by AMOS given in table 5-19. Thus, it can be seen that the model satisfies the condition that it is overidentified a necessary condition suggested by Ullman and Bentler (2012) in order to proceed with the analysis of the model.

The next test conducted to identify the model was to check whether the model is recursive. An identified model is expected to have no feedback loops amongst the latent dependent variables. A recursive model indicates that there are no feedback loops in the model and hence the model is identified. A feedback loop means that the relationship between the latent dependent variables is two-directional. For instance, in the model in figure 5.4, motivation will determine continuous intention to adopt and continuous intention to adopt will determine motivation if there is a feedback loop and will be represented as (MOT$\rightleftarrows$CI). In addition, in a recursive model error terms are not correlated. For instance, in the model in figure 5.4, the error terms e9 and e12 should not be correlated if the model is identified and recursive as there is no underlying theory that can explain the correlation (Ullman & Bentler, 2012). The test report from AMOS in table 5-20 shows that the model is recursive.

Table 5-20: Amos report on the recursive nature of the model in figure 5.4

Notes for Group (Group number 1)
The model is recursive
Sample size = 354

Another important condition that needs to be satisfied is the absence of multicollinearity. This was checked in section 5.7, and it was shown that multicollinearity is absent in the model. At this stage, it is reasonable to conclude that the model is identified. This also concludes model analysis (model estimation). The next section that needs to be taken is to test the fitness of the model to data through which the model is evaluated.

5.13. Model fitness (Model evaluation)

According to Kline (1998) it is necessary to evaluate the identified model to know that the model is ready for conducting the path analysis. Model fitness indicates to what extent the model fits the data and is essential to be examined to see that the structural equation model fits the data. If not, the measurement model is modified and assessed. This process is continued until the structural model is having a good fit for the data. The model evaluation or checking of its fitness was achieved through AMOS (Abramson et al., 2005). Literature shows that model fitness is assessed using four different tests namely measure of parsimony (Ornelas et al., 2021; Byrne, 2013), comparing the identified model with a baseline model (Ornelas et al., 2021; Byrne, 2013; Gelabert et al., 2011), testing the goodness fit of the model (Maydeu-Olivares & Garcı´a-Forero, 2010) and testing the sample discrepancy function (Supandi et al., 2021) and population discrepancy measure (Li et al. 2020). Each one of these tests is discussed next which includes the purpose of all those tests.

5.14. Measuring Parsimony

Models need to be simple to assess. A model is said to be parsimonious when the summary of the relationships between the variables in a structural model is parsimonious. It is measured by comparing the degrees of freedom in a model to the number of parameters (Falk & Muthukrishna, 2020; Weston & Gore, 2006). However, while trying to achieve parsimony, literature shows that the model fit to the data could be affected (Hooper et al., 2008). This informs the researcher that parsimony must be achieved alongside a good fit of the model to the data. In order to test both the parsimony and model fit, AMOS reports were used. Tables in 5.21 provide the AMOS reports.

Table 5-21: Fitness indices

CMIN

Model	NPAR	CMIN	DF	P	CMIN/DF
Default model	78	1281.213	357	.000	3.589
Saturated model	435	.000	0		
Independence model	29	9213.943	406	.000	22.694

Baseline Comparisons

Model	NFI Delta1	RFI rho1	IFI Delta2	TLI rho2	CFI
Default model	.861	.842	.896	.881	.895
Saturated model	1.000		1.000		1.000
Independence model	.000	.000	.000	.000	.000

RMSEA

Model	RMSEA	LO 90	HI 90	PCLOSE
Default model	.086	.081	.091	.000
Independence model	.248	.244	.252	.000

Table 5-21 shows that the degrees of freedom (DF) are found to be 357 while the number of parameters (NPAR) are found to be 78 for the default model which is the research model. That is to say that the number of parameters is far fewer than the degrees of freedom. This indicates that the model is satisfying the condition that it is parsimonious (Weston & Gore, 2006). However, the model fitness figures are not found to be acceptable. For instance, the IFI, CFI and RMSEA figures did not meet the minimum conditions. That is, widely accepted values of IFI and CFI are >0.9 while that of RMSEA is ≤ 0.08 (section 5.9). CMIN which is the chi-square measure of model fit was found to indicate a lack of fitness with a p-value of significance found to be less than 0.05. Additionally, literature shows that the measure CMIN/DF, which is another measure of model fit (Anand, 2021), needs to be improved as the acceptable value of CMIN/DF should be less than 3 (Ornelas et al., 2021; Nguyen et al., 2021) whereas the value achieved in this research is 3.589. Thus, it can be seen that there is a need to improve the goodness fit of the model. One way to improve the CMIN/DF is to use the modification indices to measure a facility available with AMOS software (Arbuckle, 2021). Although the use of modification indices is suggested by literature some researchers have cautioned against the overuse of modification indices. For instance, Arbuckle (2021) cautions that overuse of modification indices could lead to the AMOS software producing an incorrect model with a chi-square value that is acceptable, an argument supported by other researchers (e.g., MacCallum et al., 1992). The researcher was conscious of this limitation and accordingly applied the facility of modification index.

The use of the modification index enables the researcher to estimate the change in the λ^2 which is the CMIN (Chi-squared) value (Nguyen et al., 2021) reported by AMOS when the model restrictions are relaxed by way of freeing some parameters that were fixed in the initial model (Schermelleh-Engel & Moosbrugger, 2003). According to Schermelleh-Engel & Moosbrugger (2003), each modification index generated by the software has a λ^2 distribution with a degree of freedom = 1. Further, it measures the anticipated decrease in the λ^2 value when a parameter under investigation is freed from the model and the model is reestimated. In a reasonably good model, the largest modification index will be linked to that parameter that can improve the fit most when it is set free, and a good model is expected to have modification indices approaching one. However, literature shows that modification indices should be used with caution and that altering the model using modification indices should be supported by theory and should not be attempted for the sake of achieving acceptable CMIN/DF value only (Schermelleh-Engel & Moosbrugger, 2003). The report produced by AMOS on the modification index shows that to improve the CMIN/DF value the items RA4, RA2, RA1, CMP3, MOT3, TRN2, TRN3, TR1, OBS4 were freed from the model and re-estimated the model. The resulting model fit of CMIN/DF was still reported by AMOS as 3.101 which is greater than the acceptable value of <3.0. However, there are counterarguments in the literature which say that acceptable values of CMIN/DF <5.0 (Marsh & Hocevar, 1985 cited in Smrekar et al. 2020). Despite such inconsistencies in the literature, in this research the minimum acceptable value of CMIN/DF <3.0 was adhered to. Keeping this in view, the literature was further reviewed, and it was found that since CMIN/DF is a goodness fit measure if other goodness fit measures. For instance, although RA1 (Using an IoMT application enables me to complete tasks faster) has been relieved, it does not affect the measurement of the latent construct relative advantage to a greater extent as it is covered by RA6 (Using IoMT increases my productivity) an argument that is echoed by others (Sima et al., 2020; Madakam et al., 2019). Despite this, the reestimated model did not fit the data as can be seen by the CMIN/DF <3.101. Any further application of the modification index test was not yielding better results and hence no further element was freed, and the focus shifted to other fit indices.

Thus, in order to overcome the problem of a higher than 3.0 value of CMIN/DF, the researcher inspected the other model fit indices reported by AMOS to check the parsimonious nature of the model. For instance, from table 5-22 it can be seen that other models fit indices including NFI, IFI, TLI and CFI were found to satisfy the requirements of model fit with all of them found to exceed the acceptable value of 0.9 (section 5.9). In addition, the RMSEA value was found to be lower than 0.08 thus confirming the model fit and hence the parsimonious nature of the model. Further to this, the identified model was compared with a baseline model.

As far as the baseline comparisons were concerned it must be noted that AMOS produces the three models namely the default model, the saturated model and the independence model (see section 5.12) whose fitness indices provide a comparison between those models. Such a comparison enabled the researcher to know whether the goodness fit indices are approaching the reference baseline model which is the saturated model. Literature shows that in the saturated model the number of free parameters is equal to the sum of the number of variances and covariances in the model leading to a λ^2 = zero (Schermelleh-Engel et al., 2003). Furthermore, the literature shows that the independence model is a restrictive model wherein all factor loadings are made equal to one and assumed that all variables are not correlated. Literature also shows that an independence model assumes that all observed variables are free of error (Schermelleh-Engel et al., 2003).

Taking into consideration the above arguments, and from table 5-22, it can be seen that the default model, which is the research model, is found to meet the minimum requirements of the model fitness in regard to NFI, IFI, TLI and CFI with measured values exceeding 0.9, the acceptable value set for this research (see section 5.9). Additionally, RMSEA values were measured as 0.077 which is lower than the acceptable value of 0.08 set for this research (section 5.9). When compared to the reference model which is the saturated model, it can be seen that NFI, IFI, TLI and CFI are found to be approaching the saturated model value of 1.000 indicating a good model fit. Considering the above facts, it can be concluded that the default model meets the conditions of parsimony and hence is parsimonious. Although the λ^2 value was not equal to zero it can be seen from the previous paragraph that other goodness indices were used to measure the fitness and since λ^2 is considered to be sensitive to sample size λ^2 = zero condition was not considered useful to this research. However, this aspect was offset by other goodness fit indices mentioned above an argument echoed by Joreskog and Sorbom (1989).

Table 5-22: Baseline model comparison

CMIN

Model	NPAR	CMIN	DF	P	CMIN/DF
Default model	60	465.218	150	.000	3.101
Saturated model	210	.000	0		
Independence model	20	4942.355	190	.000	26.012

Baseline Comparisons

Model	NFI Delta1	RFI rho1	IFI Delta2	TLI rho2	CFI
Default model	.906	.881	.934	.916	.934
Saturated model	1.000		1.000		1.000
Independence model	.000	.000	.000	.000	.000

RMSEA

Model	RMSEA	LO 90	HI 90	PCLOSE
Default model	.077	.069	.085	.000
Independence model	.266	.260	.273	.000

The model that resulted after achieving the parsimony is provided in figure 5.5.

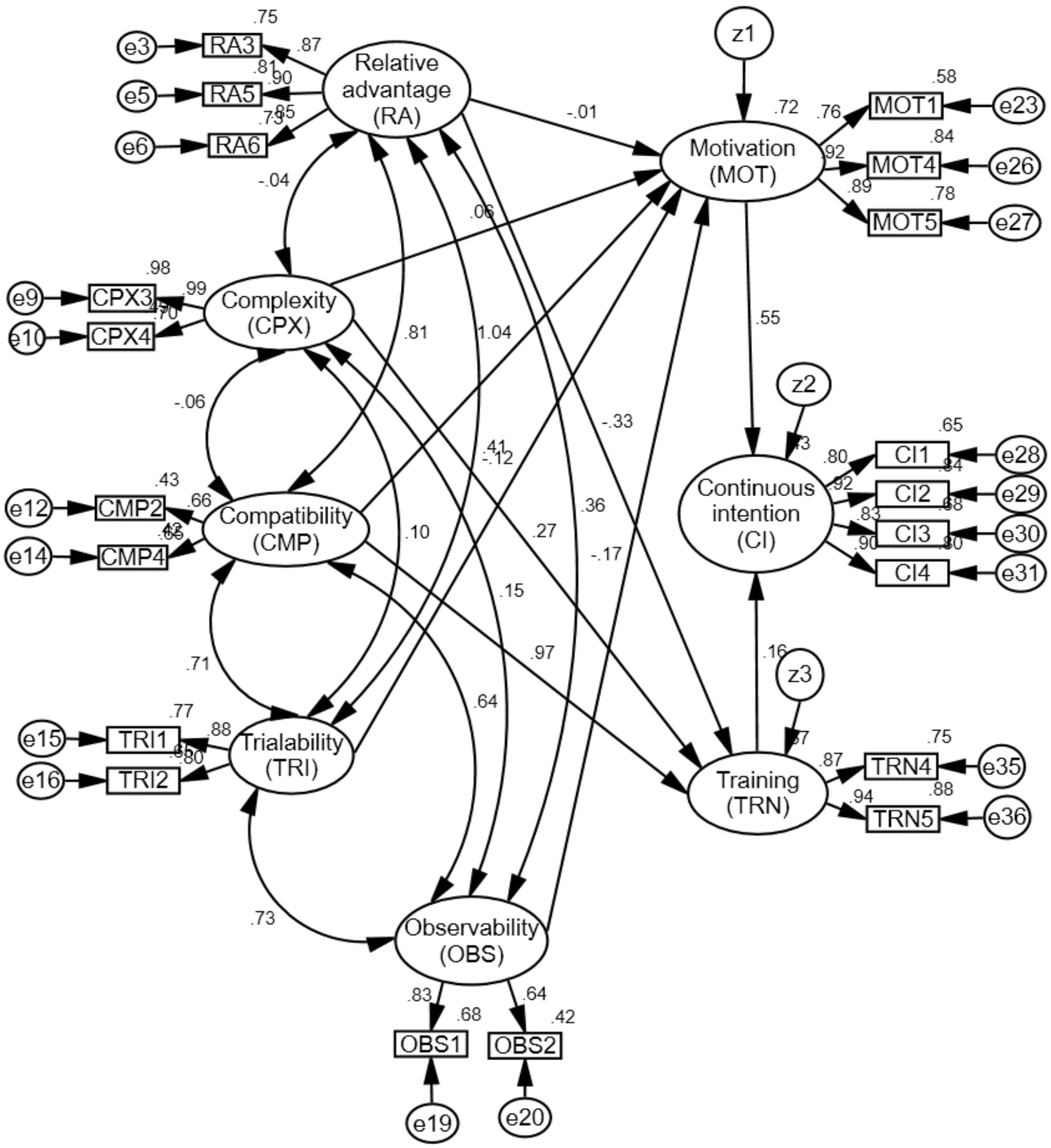


Figure 5.5: The parsimonious model.

After testing the parsimony, the researcher tested the minimum sample discrepancy function CMIN/df.

5.14.1. Minimum sample discrepancy function (CMIN/df)

According to Arbuckle (2019) the probability of a large discrepancy occurring with the present sample (under appropriate distributional assumptions and assuming a correctly specified model) is represented by the p-value which is used to test the hypothesis that the model fits the population. Further, detecting the underlying disagreement between theory and data is argued to be controlled largely by the size of the sample under discussion. For instance, in very large samples null hypotheses saying that the model fits (theory agrees with data) with the sample is likely to be rejected while for small samples the alternate hypothesis that the model does not fit the data is likely to be rejected (Cochran, 1952). In order to test these researchers, suggest the CMIN/df value be tested. Values less than 3 are accepted as indicating that there is no discrepancy in the minimum sample size while values greater than 3 indicate the presence of the discrepancy. However, in the revised model the value of CMIN/df is found to be 3.101 indicating the presence of the discrepancy. A review of the literature showed that Long, and Perkins (2003) indicate that not much importance should be laid on CMIN/df due to its heavy dependence on population size while Millis et al. (1999) argue that it is an unrealistic standard. However, where one encounters a problem of rejecting the null hypothesis when using CMIN/df, if one takes the above arguments of Long and Perkins (2003) and Millis et al. (1999) then it is prudent to turn to the suggestions given by Joreskog and Sorbom (1989). According to Joreskog and Sorbom (1989), it is worthwhile to consider the other goodness fit measures rather than using CMIN/df as indicating the minimum sample discrepancy function. Thus, according to table 5-22, it can be seen that the best fit measures NFI, IFI, TLI and CFI are all above 0.9 indicating acceptable goodness fit and hence satisfying the minimum sample frequency function requirements. After testing the minimum sample frequency test, the population discrepancy measure assessment was carried out using RMSEA. This is discussed next.

5.14.2. Population discrepancy function (RMSEA)

Hu and Bentler (1999) explain that RMSEA is an index that provides an estimate of the discrepancy between the population and model -implied population covariance matrix per degree of freedom. According to Arbuckle (2021), the population discrepancy function provides an indication of model adequacy. RMSEA was first propounded by Steiger and Lind (1980). The literature says that RMSEA provides a measure of population discrepancy function and provides an indication of the discrepancy between the observed and covariance matrix by the degrees of freedom (Montoya & Edwards, 2019; Browne & Cudeck, 1992; Steiger & Lind, 1980). RMSEA is also found to be a better index than other baseline indices as it is considered to be an absolute fit index because it is not linked to any baseline model directly (Montoya & Edwards, 2019). Furthermore, RMSEA is a measure that can indicate the amount of unexplained variance or residual in a model (Suhr, 2006). An important feature of RMSEA is that it takes into account model complexity which reflects the degrees of freedom. An important advantage of RMSEA is that it is least affected by sample size (Marsh et al., 2004; Schermelleh-Engel and Moosbrugger, 2003. Limitations of RMSEA include concerns related to sensitivity to outliers (Chai & Draxler, 2014).

The RMSEA also takes the model complexity into account as it reflects the degree of freedom as well. RMSEA value smaller than 0.05, can be said to indicate a convergence fit to the analysed data of the model while it indicates a fit close to good when it produces a value between 0.05 and 0.08 (Cangur & Ercan, 2015). An RMSEA value falling between the range of 0.08−0.10 indicates a fit that is neither good nor bad. Hu and Bentler (1999) remarked that the RMSEA index smaller than 0.06 would be a criterion that will suffice. A few researchers argue that RMSEA is a fit index which is affected the least by sample size (Marsh et al., 2004; Schermelleh-Engel and Moosbrugger, 2003). However, there is no consensus on the cutoff value of RMSEA in the literature. For instance, MacCallum et al. (1996) suggest that a value less than 0.08 indicates a good fit while Steiger (2007) suggests a cut off value of 0.07 and Hu and Bentler (1999) suggest a cut off value of 0.06. As far as this research is concerned the cutoff value of RMSEA was fixed at 0.08 as indicating goodness of fit based on the recommendations of MacCallum (1996). From the results provided in table 5-22, it can be seen that the respecified parsimonious model was shown to have an RMSEA of 0. 077, which is an acceptable goodness fit.

At this point, it can be seen that the researcher has provided ample evidence of model of the model fit although there is no clear indication of what fitness indices need to be considered to determine that a model fits the data clearly. Therefore, it has become a practice amongst researchers involved in testing a structural model's fitness to data to report as many fitness indices as possible to show that the model fits the data (Kline, 1998). Thus, this research has reported the IFI, TLI, CFI and RMSEA indices to show that the model fits the data. It can be said that the structural model has been evaluated by applying the necessary statistical tests on the model. Thus, based on the completion of the two essential steps of model analysis (estimation) and model fitness (evaluation) it can be concluded that the respecified model is ready for further analysis. As a next step, the research proceeds to analyse the various relationships in the research model and the expected directions of those relationships as suggested by Bollen and Long (1993) using path analysis.

Arbuckle (2021) argues that the minimum number of observed variables required to conduct CFA is two per latent variable. As far as the reliability of the latent constructs is concerned, it can be seen that the construct reliability is measured using squared multiple correlations. This step has been repeated at the structural measurement level which takes into account the reliability of the measurements once the confirmatory model has been finalised. For instance, from figure 5.5 it can be seen that the CFA model has led to a newly specified model which has been used to conduct the structural and path analysis of the model. Figure 5.5 shows the structural model. In the structural model in figure 5.5, it can be seen that there are two constructs namely complexity and trialability as being measured using only two items each. However, the squared multiple correlation table generated by AMOS (table 5-18) shows that the SMC values are above the accepted value of ≥0.3 which indicate that construct reliability has been achieved and that there is no impact of removing certain items from the original model on the reliability aspect.

5.14.3. Path Analysis

Chang et al. (2020) explain that in SEM path analysis is a procedure that can help estimate the relationships among latent constructs namely relative advantage, complexity, compatibility, trialability, observability, motivation, training, and continuous intention to use, AI awareness, and novelty seeking. Age is measured directly and hence is not considered a latent variable. However, the path analysis of the independent, mediating and dependent variables on the one hand and the moderators in the model on the other have been dealt with separately to reduce complexity. Thus, in this section, the path analysis is explained with regard to the independent, mediating and dependent variables only. As per the identified model in figure 5.5 the following paths will be analysed (tables 5.23 and 5.24):

Table 5-23:Paths to be analysed between independent and mediating variables:

Independent variables		**Mediating variables**
Relative advantage	→	Motivation (MOT)
Complexity (CPX)	→	Motivation (MOT)
Compatibility (CMP)	→	Motivation (MOT)
Observability (OBS)	→	Motivation (MOT)
Compatibility (CMP)	→	Training (TRN)
Relative advantage (RA)	→	Training (TRN)
Complexity (CPX)	→	Training (TRN)
Trialability (TRI)	→	Motivation (MOT)

Table 5-24: Paths to be analysed between mediating and dependent variables

Mediating variables		**Dependent variable**
Motivation (MOT)	→	Continuous intention (CI)
Training (TRI)	→	Continuous intention (CI)

The paths were analysed using AMOS and the path coefficients were tabulated. The valid paths were identified as those paths whose path coefficients were found to be statistically significant with a p-value less than or equal to 0.05. Table 5-25 provides the details of the analysed paths.

Table 5-25: Statistically significant and insignificant paths with path coefficients and p-value

			Estimate	**S.E.**	**C.R.**	**P**	**Label**
Motivation_(MOT)	<---	Relative_advantage_(RA)	-.006	.207	-.029	.977	par_14
Motivation_(MOT)	<---	Compatibility_(CMP)	1.319	.458	2.880	.004	par_17
Motivation_(MOT)	<---	Trialability_(TRI)	-.097	.102	-.947	.344	par_24
Motivation_(MOT)	<---	Complexity_(CPX)	.068	.073	.936	.349	par_26
Training_(TRN)	<---	Complexity_(CPX)	.349	.079	4.414	***	par_27
Motivation_(MOT)	<---	Observability_(OBS)	-.197	.152	-1.297	.195	par_28
Training_(TRN)	<---	Relative_advantage_(RA)	-.343	.174	-1.975	.048	par_30
Training_(TRN)	<---	Compatibility_(CMP)	1.472	.292	5.049	***	par_31
Continuous_intention_(CI)	<---	Training_(TRN)	.152	.056	2.734	.006	par_11
Continuous_intention_(CI)	<---	Motivation_(MOT)	.621	.076	8.217	***	par_12

From table 5-25, it can be seen that the paths RA→TRN, CPX→TRN, CMP→MOT, CMP→TRN, TRN→CI and MOT→CI are statistically significant with p-value of significance found to be less than 0.05 while the paths RA→MOT, CPX→MOT, TRI→MOT and OBS→MOT were not found to be statistically significant. In order to test the variance of endogenous variables using the SMC, the AMOS report was used which is presented in table 5-26 (Arbuckle, 2021).

Table 5-26: Testing the variance of endogenous variables

Constructs	Function of the endogenous variables	Estimate
Training_(TRN)	Mediating	.574
Motivation_(MOT)	Mediating	.722
Continuous_intention_(CI)	Dependent variable	.430

The results of the readings tabulated in table 5-26 can be interpreted as follows:

The three exogenous variables namely RA, CPX and CMP together account for a variance in TRN to the extent of 57.4%. Similarly, the five exogenous variables RA, CPX, CMP, TRI and OBS together account for a variance of 72.2% in MOT. Using the arguments of Kline (1998) who categorises the variance as small (variance between 0.1 and 0.29), moderate (variance between 0.3 and 0.49) and large (≥0.5) it is possible to account for the variance reported by AMOS. For instance, RA, CPX and CMP together account for a large variance (0.574) in TRN which means that the relative advantage, complexity and compatibility of IoMT have a large effect on the training of healthcare professionals, expected to improve their continuous intention to use IoMT. Especially when IoMT is embedded with AI, then using IoMT devices could be challenging for the users without training and training becomes paramount and those users may resist using the latest technology. On the contrary, even after embedding AI in IoMT, if the users find using IoMT user friendly, then the training requirements related to using IoMT will diminish dramatically. For example, wearables that measure blood pressure are employed in patients and have the ability to make decisions to advise the patients related to activities concerning blood pressure with the support of IoMT, then the healthcare professionals will be able to provide more accurate health services and hence improve patient care. On the contrary, if IoMT is not supported by AI that is less complex (easiness in logging the readings from multiple devices accurately), has high relative advantage (accurate measurement of health parameters) and has high compatibility (fewer problems of interoperability between devices) then the healthcare professionals could be concerned in using such devices due to lack of appropriate knowledge on how to use the devices. Similar arguments can be advanced with regard to motivation as the large variance accounted for in motivation (72% = 0.722) by the five independent variables is even higher than training in IoMT implying that when the wearables have a high relative advantage and high compatibility then motivation increases in healthcare professionals to continue to use IoMT.

Finally, the five independent variables RA, CPX, CMP, TRI and OBS together account for a variance of 43% in the dependent variable continuous intention to use. This indicates that when there is a change of one unit in each one of the independent variables then there is a 0.403-unit change that could occur in continuous intention to use IoMT by healthcare professionals in the positive direction. It must be mentioned here that the extent to which the independent variables account for a variance of 43% in the dependent variable has two components. One is the set of statistically significant paths RA→MOT, CPX→TRN, CMP→MOT, CMP→TRN, TRN→CI and MOT→CI. The other is the statistically significant covariance or the association that exists between the exogenous variables (table 5-27). It is useful to mention here that exogenous variables like TRI and OBS which do not have statistically significant paths to the dependent variable can still contribute to the model as associates of the remaining three exogenous variables. That is to say, taking into account the statistically significant relationships that exist between the independent and dependent variables on the one hand and the covariance that exists among the independent variables on the other (table 5-28), it is possible to argue that there is a moderate change that will occur in continuous intention to use when the independent variables are adjusted. Here the statistically significant associations OBS↔TRI, TRI↔CMP, CMP↔OBS, RA↔TRI and RA↔OBS add to the variance accounted for in the dependent variable by the exogenous variables implying that these associations provide meaning to the variance accounted for by the independent variables in the dependent variable.

Covariances: (Group number 1 - Default model)

Table 5-27: Covariance amongst the exogenous variables of the structurally identified model

			Estimate	S.E.	C.R.	P	Label
Observability_(OBS)	<-->	Trialability_(TRI)	.561	.074	7.559	***	par_13
Compatibility_(CMP)	<-->	Trialability_(TRI)	.481	.064	7.508	***	par_15
Compatibility_(CMP)	<-->	Complexity_(CPX)	-.031	.035	-.883	.377	par_16
Trialability_(TRI)	<-->	Complexity_(CPX)	.078	.051	1.534	.125	par_20
Observability_(OBS)	<-->	Compatibility_(CMP)	.311	.050	6.238	***	par_21
Relative_advantage_(RA)	<-->	Compatibility_(CMP)	.512	.060	8.509	***	par_22
Relative_advantage_(RA)	<-->	Trialability_(TRI)	.412	.067	6.176	***	par_23
Observability_(OBS)	<-->	Complexity_(CPX)	.083	.045	1.858	.063	par_25
Relative_advantage_(RA)	<-->	Observability_(OBS)	.256	.053	4.808	***	par_29
Relative_advantage_(RA)	<-->	Complexity_(CPX)	-.031	.042	-.744	.457	par_32

The meaning of the contribution of the association between exogenous variables could be explained as follows. Taking the example of the statistically significant association namely CMP↔OBS it can be seen that if OBS changes CMP will change and vice-versa. This implies that when OBS changes, CMP will change which in turn will influence CI to change indicating that the association between OBS and CMP will practically affect the relationship between CMP and CI. For instance, observability could indicate the act of the healthcare professionals to see and understand the function and application of the IoMT devices (e.g., wearables) when professionals are using those devices and apply them as part of patient care. When the healthcare professionals observe more and more, then their ability to apply those IoMT devices improves. This in turn is expected to improve the CMP of IoMT. This will then affect the relationship between CMP and CI, improving CI. That is to say OBS as a variable can contribute in the determination of CI. Similar arguments can be advanced against the association of TRI with other exogenous variables.

Next, the analysis proceeds to understand the relative effect of each one of the exogenous variables on the dependent variable using the standardised regression weights generated by AMOS. This step provides the basis to clearly explain the extent to which independent variables can be used to determine CI one by one (table 5-28).

Standardised Regression Weights: (Group number 1 - Default model)

Table 5-28: Standardised regression weights of the relationship between the exogenous variables and CI.

			Estimate
Motivation_(MOT)	<---	Relative_advantage_(RA)	-.007
Motivation_(MOT)	<---	Compatibility_(CMP)	1.036
Motivation_(MOT)	<---	Trialability_(TRI)	-.120
Motivation_(MOT)	<---	Complexity_(CPX)	.062
Training_(TRN)	<---	Complexity_(CPX)	.268
Motivation_(MOT)	<---	Observability_(OBS)	-.174
Training_(TRN)	<---	Relative_advantage_(RA)	-.330
Training_(TRN)	<---	Compatibility_(CMP)	.967
Continuous_intention_(CI)	<---	Training_(TRN)	.162
Continuous_intention_(CI)	<---	Motivation_(MOT)	.552

The interpretation of the results produced by AMOS follow which in turn lead to examining whether the hypotheses developed for this research are supported or rejected. Out of the ten relationships that exist in the theoretical model, four relationships were found to be statistically insignificant namely RA→MOT, CPX→MOT, TRI→MOT and OBS→MOT. With regard to the remaining statistically significant relationships, it can be seen that CMP is having a positive relationship with motivation and the regression coefficient indicates a large and significant relationship between the two constructs (>0.5). This indicates that when the compatibility of IoMT devices (e.g., wearables) with the users' requirements or other devices employed in the provision of healthcare is high, then the healthcare professionals are likely to be highly motivated to use the IoMT devices. For example, Celic and Magjarevic (2019) explained that IoMT devices should be compatible with existing nodes and users should be aware that the continuous connectivity and exposure to a higher number of smart devices, connected to a node, could make the users vulnerable to privacy and security threats. In this example, if the findings of this research are applied, then it can be seen that if the compatibility of IoMT devices used by the healthcare professionals is high with the existing nodes, then the motivation of the healthcare professionals to continuously use IoMT is expected to be high.

Similarly, the complexity of IoMT is positively and significantly related to the training aspects of IoMT with the strength of the relationship indicated by the regression coefficient (0.268) classified as small (<0.3). This is an important finding. The finding indicates that the influence of complexity involved with the use of IoMT on training required for users to handle or operate or use IoMT is small meaning the complexity of IoMT may not be a major problem for users. Therefore, users may feel highly motivated to use IoMT. For example, Stieninger et al. (2018) argue that complexities associated with security challenges in devices including IoMT devices can affect the adoption of an innovation. Aldosari et al (2016) found out in their research that security aspects could contribute to security difficulties while data exchange takes place between IoT devices when single solutions are being designed. These arguments indicate that training is needed for the users to understand what problems could arise while implementing IoMT for healthcare purposes, and how to deal with complexities and resolve issues. This implies that the higher the complexity of IoMT devices, the higher the training required to resolve complex issues that could arise as a result of using those IoMT devices. This finding highlights the need to understand the complexities associated with IoMT during the process of diffusion and introduce training to healthcare professionals at the time of the diffusion of IoMT rather than after the acceptance of IoMT.

The outcome of the data analysis shows that relative advantage as a diffusion parameter is negatively and significantly related to the training of healthcare professionals (see table 5-28) with the strength of the relationship indicated by the regression coefficient (-0.33) classified as moderate (>0.3 but < 0.5). This finding perhaps is a contradiction as usually training is provided generally to gain awareness about the relative advantages associated with IoMT. This implies that the higher the relative advantage, the higher should be the level of training for the users. However, there are instances where technological aspects could vanish into the background and non-technical aspects could come to the fore. One such aspect that concerns IoMT is the security aspect. For instance, Weinberg et al. (2015) argue that the development of sensor-rich devices used in IoT has led to difficulties in controlling privacy aspects due to the high volume and speed of data transmitted between organisations. This argument shows that when IoMT offers relatively higher technical advantages relative to legacy systems, security issues could ground those relative advantages, making those advantages redundant. In such a situation training plays an important role to create awareness about the problems associated with IoMT. Echoing similar sentiments Chen and Zhang (2016) argue that gaining a relative advantage but at the cost of privacy is a challenge for organisations and such situations could lead to IT leaders facing security violations after adopting innovations which affect business. To overcome such situations researchers, suggest that training be given to users to create awareness about the challenges (Altadonna, 2020; Ghazvini & Shukur, 2016). This implies that in situations where IoMT provides a relatively higher advantage technically and is adopted, yet if provision training is lower then such a situation can cause challenges to the healthcare service providers using those IoMT devices. On the contrary, if the relative advantage of IoMT is technically lower, then users must be given higher-level training to deal with the situation. These arguments explain the significance of the negative relationship between RA and TRI. While research outcomes in the literature that have discussed the relationship between RA and TRI are far and few, those outcomes are contradictory. For instance, Putteeraj et al. (2021) point out that in the context of e-health, complexity surrounding the technology in regard to data handling may require rigorous training leading to a negative relationship between adoption and also a relative advantage. This implies that the higher the relative advantage, the lower the complexity and hence lower the rigour in training. These arguments show the inverse relationship between relative advantage and training in technology. However, in another study by Mairura (2016) conducted in the context of automobile mechanics in micro and small enterprises in Kenya, RA was found to be directly linked to the training status of the mechanics with 82 percent of the mechanics agreeing to this fact. Amidst these contradictions, the results of this research show that the findings are similar to those of Putteeraj et al. (2021).

Furthermore, the results show that compatibility as a diffusion parameter is positively and significantly related to the training of healthcare professionals with the strength of the relationship indicated by the regression coefficient as (0.967) classified as large (>0.5). The finding shows that compatibility plays a significant role in the training of healthcare professionals using IoMT. This can be demonstrated by a practical example. Islam et al. (2015) argue that vendors dealing in IoMT do not follow standard rules and regulations for compatible interfaces and protocols. This can cause interoperability problems. In such situations, it is essential to ensure that training is given to the mechanics and users on being aware of the interoperability problems and how to handle the IoMT devices to ensure that there are no difficulties while using the IoMT devices. For instance, literature shows that smartphone applications (apps) for patients and general healthcare are supported by medical education, training, and auxiliary apps (Mosa et al., 2012). Bannan et al. (2017) explain that it is challenging to train healthcare professionals in general. This implies that even if there are compatibility is high, then training still could be a challenge indicating that the greater the compatibility, the higher could be the necessity to get trained. Especially if many applications are developed and provided on the mobile phone as part of IoMT in a short period, then it is possible that healthcare professionals and patients may find compatibility problems between applications and rigorous training may be needed. Thus, it can be seen that the finding of this research with regard to the relationship between compatibility and training are aligned with previous research outcomes found in the literature (Fornasier, 2019).

However, there can be contradictory effects also. For instance, Singh (2018) argues that sometimes trained healthcare professionals focus on the wrong areas of training instead of focusing on patientcare, for instance focusing on raw data than focusing on helping patients make decisions about lifestyle. This implies that training is not helping the professionals to focus on patientcare indicating the irrelevance of the compatibility factor, a finding that is not widely reported in research papers. These findings indicate that, despite rare opposing views, it can be concluded that the compatibility of IoMT is a major factor that influences the training factor positively.

Further to discussing the relationship between exogenous variables and the mediating variables, this section analyses the results related to the relationship between the mediating variables and the dependent variable. Thus, it can be seen that motivation as a behavioural attribute is positively and significantly related to the training of healthcare professionals with the strength of the relationship indicated by the regression coefficient as (0.552) classified as large (>0.5). That motivation is strongly related to continuation intention to use IoMT is in line with similar findings of other researchers (Ferriz-Valero et al., 2020; Kupfer et al., 2016; Jin et al., 2013). Practical examples of motivation as a factor that influences continuous intention to use IoMT or acceptance of IoT devices in the medical field are found in the literature. For instance, Çolak and Kağnıcıoğlu (2021) point out that there are research publications that have found that motivation positively impacts behavioural intentions towards using smartwatches. Similar sentiments have been echoed by Irfan and Ahmad (2018) who argue that motivations lead medical practitioners to decide to adopt IoMT. There are contradictory arguments that motivation does not influence acceptance and continuous use of IoMT. For instance, Prasetyo et al. (2021) in their research on the acceptance of medical education e-learning platforms during the COVID-19 pandemic in the Philippines found that hedonic motivation does not impact the behavioural intention to use e-learning platforms. Whilst there are contradictory findings in the literature i.e., regarding the influence of motivation on continuous intention to use or accept or adopt IoMT, the findings of this research align with the findings of Ferriz-Valero et al. (2020), Kupfer et al. (2016) and Jin et al. (2013).

Furthermore, it can be seen from the findings of this research that motivation successfully mediates between compatibility and continuous intention to use IoMT. That is to say that during diffusion of IoMT, it is compatibility that matters most i.e., as an independent variable that drives motivation, which in turn motivates continuous intention to use. For instance, there is evidence in the literature to show that with regard to diffusion it is the early adopters who are motivated to use innovations (Bhat et al., 2021). According to Bhat et al. (2021), compatibility, relative advantage and complexity impact motivation in regard to the behavioural intention of users to accept and use an innovation like wheelchair supported by IoT at the beginning of the diffusion. While the findings in this research do not support the impact of relative advantage and complexity on motivation, at the same time, it finds support from Bhat et al. (2021) regarding the positive relationship between compatibility, motivation and continuous intention to use IoMT. The reason why relative advantage and complexity did not find as significant determinants of motivation and continuous intention to use IoMT could be that healthcare professionals might have felt that relative advantage and complexity of IoMT are already built into the IoMT devices and have been addressed by the manufacturer of IoMT devices. However, problems like interoperability between IoMT devices, which require to be dealt with by the technicians as well as the users, and are directly linked to compatibility, impact motivation to continuously use IoMT.

Further to discussing the relationship between motivation and continuous intention to use IoMT, this section deals with the results concerning the relationship between training in

IoMT and continuous intention to use IoMT. Training IoMT as a behavioural attribute is positively and significantly related to the training of healthcare professionals with the strength of the relationship indicated by the regression coefficient as (0.162) classified as small (>0.1 but <0.3). That training is having a relationship with continuous intention to use whose strength is considered small finds support from other researchers (Bhardwaj et al., 2021; Huang et al., 2020; Venkatesh et al., 2003). In practical terms literature clearly shows that training plays an important role in ensuring the adoption or acceptance and use of IoMT (Rajmohan & Johar, 2020). Literature shows that virtual-reality could be used to train healthcare professionals (Yaacoub et al., 2020) to perform various realistic operations employing IoMT, for instance in simulated training (McCarth & Uppot, 2019), emergency training (Munzer et al., 2019) and cardiopulmonary resuscitation training (Balian et al., 2019) that employ IoMT. While these examples show that training is an essential part of continuous intention to sue IoMT, there are counterarguments that indicate that training alone is not enough to ensure that healthcare professionals continue to use IoMT. For instance, Gorozidis and Papaioannou (2014) argue that motivation and training are interrelated and showed in their research concerning teachers' motivation to participate in training and to implement innovations that both controlled and autonomous motivation to be trained influence intentions to be trained. This argument shows that training and motivation are interrelated and any research involving motivation must involve training in the research. Thus, it is possible to conclude that any research outcome involving training must involve motivation. This implies that the results obtained in the research, with regard to training as influencing continuous intention to use IoMT in isolation, may provide an incomplete picture. Taking this criticism into consideration, this research argues that the results of motivation and training must be read in conjunction to understand the influence of either factor on continuous intention to use IoMT.

Furthermore, it is important to note that training as a mediator has been found significant in this research. It is seen that all the three exogenous variables namely relative advantage, complexity and compatibility are found to have a statistically significant relationship with training in IoMT, which indicates that during diffusion of IoMT, training in IoMT appears to be an essential mediator of the relationship between the three diffusion factors and continuous intention to use IoMT. This is a very new finding and indicates the extent to which training plays an important role in helping IoMT diffuse, leading to a better rate of adoption and continuous intention to use IoMT. Finally, it can be seen that no similar research results have been found in the extant literature that has discussed the mediating effect of training between diffusion factors depicted by diffusion of innovation theory and continuous intention to use IoMT. In practical terms, it can be interpreted that IoMT embedded with complex technologies like AI (monitoring patient impulses via healthcare monitoring systems which are expected to aid doctors in offering good quality healthcare support using IoMT (Aldahiri et al., 2021) with relative advantage, compatibility and low complexity will diffuse to the stage of continuous intention to use IoMT of healthcare professionals, through appropriate training. This is supported by the diffusion theory, which says that the diffusion of innovation and its adoption or non-adoption depends on three correlates; namely characteristics of the potential individual adopter, perception of the individual about the innovation and the features of the social system or organisation where the potential adopter resides (Bakkabulind, 2014; Rogers, 2003). According to Bakkabulindi (2014), one of the characteristics of the potential adopter is the level of training of relevance to the innovation the person has received. Thus, it can be argued that the dominating and mediating ability of training as a construct in the model during the diffusion of IoMT is driven by relative advantage, complexity and compatibility, leading to continuous intention to use or adopt IoMT can be explained. The lack of support for motivation as the main mediator can be explained by the expectancy theory which links training as a driver of motivation (Abadi et al.2011). This implies that where training is dominant in a model, motivation could be said to be derived by the individuals like healthcare professionals to enable those healthcare professionals to develop continuous intention to adopt IoMT. In this case, training leads to motivation which implies that depicting motivation as a separate mediator not linked to training could be a weak argument.

After discussing the statistically significant relationships that influence continuous intention to use IoMT, it was found necessary to explain what was the reason that the relationships RA→MOT, CPX→MOT, TRI→MOT and OBS→MOT did not have statistically significant relationships. The relationships RA→MOT and CPX→MOT could have been found to be insignificant due to the fact that the relative advantage and complexity of IoMT were not sufficiently strong to motivate healthcare professionals to use IoMT as those users might require to undergo training to understand the IoMT and how to use it. Without such knowledge and awareness about IoMT and the latest AI technology embedded in it, it might not have been possible for the users to get motivated and use IoMT. This can be explained by the statistically significant relationships established in this research namely RA→TRN and CPX→TRN. These two relationships clearly point out that if healthcare professionals have to understand the relative advantage of AI-based IoMT and the complexity of the technology built into it, then the results of the research point out that both relative advantage and complexity drive training. This implies that once the healthcare professionals are trained then those professionals would like to employ IoMT in patient care. This then points toward the positive relationship TRN→CI. Thus, it can be interpreted that from the time IoMT embedded with AI starts diffusing, then training helps the healthcare professionals to understand IoMT and how to use it leading to continuous intention to use IoMT. In addition, it must be noted here that compatibility was already found to be statistically significantly related to training. That is to say that all the three exogenous variables namely relative advantage, complexity and compatibility drive the training in IoMT followed by continuous intention to use IoMT. This implies training is the most important mediator that supports the diffusion of AI-based IoMT influencing the continuous intention to use IoMT whereas motivation is found to support AI-based IoMT by mediating between compatibility and continuous intention to use IoMT. This can be explained by the following example.

RFID is a device that is being used in integrating wearable IoMT devices to measure breath, blood pressure and Electro CardioGram (ECG) (Sun et al., 2016). However, the measurements need to be collected and analysed using multiple equipments which form part of IoMT architecture (see figure 5.6) (Qureshi & Krishnan, 2018).

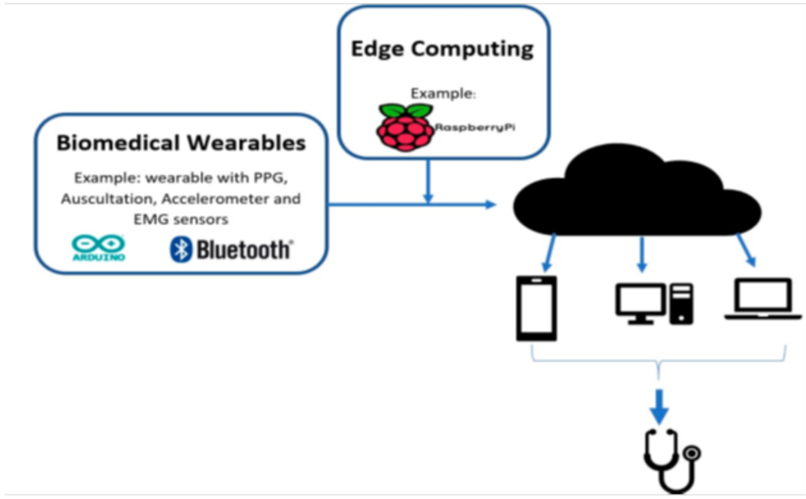


Figure 5.6: IoMT devices and interconnections (Arduino, 2021; Raspberry PI Zero, 2021)

For instance, RFID makes it possible to achieve multi-target recognition and high-speed moving object recognition used by healthcare professionals widely. As shown in figure 5.6, IoMT devices like those measuring ECG connected to the network, if implemented in healthcare systems, then training needs to be given to healthcare professionals on how to use those devices, as those devices are designed to work with the latest technologies. Healthcare professionals may not easily understand how to use those devices. There is a need for training before using them. Aspects like relative advantage, compatibility and complexity of those technologies which drive IoMT devices need to be practically understood by those professionals before they start using them. The above discussions demonstrate that training is a construct that has a greater influence on continuous intention to use IoMT rather than motivation. This is an important finding of this research. These findings are largely supported by Vroom's (1964) expectancy theory supported by Chiang and Jang (2008) which says that specific behavioural alternatives are driven by motivation and are suggested when deciding among behaviour options. Abadi et al. (2011) expanded the model of Chiang and Jang (2008), using expectancy theory and studied those influential factors on employees' motivation that were linked to participating in the in-service training courses. These arguments show that expectancy theory supports the dominance of training as a mediator during the diffusion of IoMT.

Moreover, it was found that trialability and observability do not influence motivation. Reasons for obtaining this result could be that both trialability and observability are likely to be part of the training that healthcare professionals have indicated as an important determinant of continuous intention to use IoMT and as a mediator between the three exogenous factors and the dependent variable shown in figure 5.5. Thus, the lack of statistical significance between trialability and observability could be explained. Lack of use of trialability and observability could be found in the literature, for instance, Savoury (2019) used the construct's relative advantage, complexity and compatibility only while investigating the internet adoption behaviour in the automation industry in the USA. Martins et al. (2106) explain that trialability and observability are often not included in research concerning innovation as those constructs are not considered to be solely related to the innovation diffusion process. Similar sentiments are echoed by Lee and Cheung (2004).

Further to analysing the paths between the exogenous and endogenous variables, the next step taken was to analyse the association (covariance) between the exogenous variables. From table 5-27, it can be seen that the relationships (Observability_(OBS) <--> Trialability_(TRI)), (Compatibility_(CMP) <--> Trialability_(TRI)), (Observability_(OBS) <--> Compatibility_(CMP)), (Relative_advantage_(RA) <--> Compatibility_(CMP)), (Relative_advantage_(RA) <--> Trialability_(TRI)) and (Relative_advantage_(RA) <--> Observability_(OBS)) have statistically significantly associations. This is in line with the diffusion of innovation theory. However, amongst the valid associations, the association between observability and trialability is the strongest with a correlation of 0.561. This can be interpreted that during the time of diffusion, observability, and trialability together support the covariate's relative advantage and compatibility. Regarding complexity, it can be seen that none of the other constructs has any statistically significant association with it, implying that complexity stands alone in the model as a single independent variable that directly drives the mediating variables without the support of other variables. The interpretation is that this weakens the construct complexity meaning that the predictive power of complexity reduces.

Another important inference that can be derived is that while trialability and observability were found to be statistically not significant in influencing the mediator motivation, at the same time, these two variables have a significant association with relative advantage and compatibility. That relative advantage and compatibility of IoMT are associated with both observability and trialability can be seen in the following example. For instance, when healthcare professionals want to use IoMT that involves sensory patches, medical kiosks and infant monitors it is difficult to try out as well as observe how to use those devices. These aspects require training before the healthcare professionals could use them. However, being specialized devices, the healthcare professionals can't try them out or get chances to observe how they are used. In such cases even though the two constructs do not influence motivation, they associate with relative advantage and compatibility and enable those two exogenous variables to become more powerful determinants of training and hence the continuous intention to use. This implies that when the healthcare professionals are trained and ready to use IoMT devices, then not only do those professionals understand the relative advantage and compatibility of those devices but also can observe and try out them. Thus, the combination of the covariances amongst the four diffusions of innovation variables namely the relative advantage, compatibility, trialability and observability on the one hand and the relationship between relative advantage, compatibility and training on the other provide a powerful determination of the continuous intention to use IoMT during its diffusion. That is to say, any change in any one of the exogenous variables is likely to affect training and hence continuous intention to use IoMT. This is an important finding. To the knowledge of the researcher, no similar findings are reported in the extant literature about the impact of the covariance that exists amongst the four diffusion factors relative advantage, compatibility, trialability and observability, on training and continuous intention to use IoMT. However, in other fields of study, for instance, Al-Rahmi et al. (2019) studied students' intention to use e-learning systems the five factors of diffusion have been found to be correlated to each other significantly. In another instance, Putteeraj et al. (2021) who investigated the E-Health adoption readiness in Mauritius did not find a correlation among all the five constructs. The results obtained by Putteeraj et al. (2021) show that compatibility was not found correlated to complexity and complexity was not correlated to trialability as well as observability. The research outcome of this research differs from those obtained by A-Rahmi et al. (2019) but nearly aligns with Putteeraj et al. (2021), with a complexity not correlating with compatibility, trialability and observability. This may primarily be due to the fact that IoMT being a complex technology, might not have been found to be easy to tackle by the participants in this research when compared to the other constructs. This is evidenced by the responses given by the participants. From table 5- 27 it can be seen that the responses were close to the mean of 3.0, which indicates a neutral response. This implies that complexity as a factor could obstruct the diffusion of IoMT and deter healthcare professionals from continuously using IoMT. There is a need to address this issue by making the innovation to be less complex and more user friendly.

Finally, the large covariance (0.512) that exists between relative advantage and compatibility shows that relative advantage and compatibility are important constructs that aid the diffusion of IoMT as innovation through to continuous intention to use IoMT. For instance, when a comparison is made between the commonly used method of capturing the ECG and the IoMT based ECG, it can be seen that healthcare professionals gain a relative advantage while using IoMT as data can be captured remotely and continuously leading to better patient care. In addition, the compatibility of those IoMT devices to the computers as well as other devices makes the data collection more accurate and easier for the healthcare professionals unlike the conventional methods of capturing data in person which need to be fed into the computers leading to probable errors during data entry. Thus, the covariance (Relative_advantage_(RA) <--> Compatibility_(CMP)) acts as a powerful association to influence the mediator training and the dependent variable continuous intention to use IoMT. This is an important finding. Similar findings are not reported in the literature relevant to the internet of medical things although some researchers have found a correlation between relative advantage and compatibility in healthcare contexts but not IoMT (Almohtadi & Aldarabah, 2021; Al-Rahmi et al., 2019).

From the above discussions, the following inferences could be drawn. From table 5-27 the following interpretations could be made:

- The association between relative advantage and compatibility is a large correlation.
- The association between relative advantage and trialability is a medium correlation.
- The association between relative advantage and observability is a small correlation.
- The association between compatibility and trialability is a medium correlation.
- The association between compatibility and observability is a medium correlation.

- The association between trialability and observability is a large correlation.

From table 5-25 the following interpretations could be made

- The path relative advantage (RA) → motivation (MOT) is not significant. The relative advantage of IoMT does not act as a determinant of motivation to use IoMT. Hence hypothesis H1a is rejected.
- The path relative advantage (RA) → training (TRN) is significant. The relative advantage of IoMT acts as a determinant of training to use IoMT. Hence hypothesis H1b is accepted.
- The path complexity (CPX) → motivation (MOT) is not significant. The complexity of IoMT does not act as a determinant of motivation to use IoMT. Hence hypothesis H2a is rejected.
- The path complexity (CPX) → training (TRN) is significant. The complexity of IoMT acts as a determinant of training to use IoMT. Hence hypothesis 2b is accepted.
- Path compatibility (CMP) → motivation (MOT) is significant. The compatibility of IoMT acts as a determinant of motivation. Thus, hypothesis 3a is accepted.
- Path compatibility (CMP) → training (TRN) is significant. Compatibility of IoMT acts as a determinant of training in IoMT. Hence hypothesis 3b is accepted.
- The path observability (OBS) → motivation (MOT) is not significant. Observability of IoMT does not act as a determinant of motivation. Hence hypothesis H4 is rejected.
- The path trialability (TRA) → motivation (MOT) is not significant. Observability of IoMT does not act as a determinant of motivation. Hence hypothesis H5 is rejected.
- The path motivation (MOT) → continuous intention to use IoMT (CI) is significant. Motivation acts as a determinant of continuous intention to use IoMT. Thus, hypothesis H6 is accepted.
- The path training (TRN) → continuous intention to use IoMT (CI) is significant. Training to use IoMT acts as a determinant of continuous intention to use IoMT. Thus, hypothesis H7 is accepted.

Regression Weights: (Group number 1 - Default model).

Table 5-29: Unidimensionality verification using p-value of significance and C. R. value

			Estimate	S.E.	C.R.	P	Label
RA6	<---	Relative_advantage_(RA)	1.000				
MOT1	<---	Motivation_(MOT)	1.000				
TRN5	<---	Training_(TRN)	1.051	.055	19.053	***	par_1
OBS1	<---	Observability_(OBS)	1.294	.136	9.502	***	par_2
CI1	<---	Continuous_intention_(CI)	1.000				
CI2	<---	Continuous_intention_(CI)	1.107	.053	20.895	***	par_3
CI3	<---	Continuous_intention_(CI)	.905	.051	17.763	***	par_4
CI4	<---	Continuous_intention_(CI)	1.055	.053	19.760	***	par_5
CMP2	<---	Compatibility_(CMP)	1.075	.098	10.927	***	par_6
CMP4	<---	Compatibility_(CMP)	1.000				
TRI2	<---	Trialability_(TRI)	.868	.059	14.789	***	par_7
TRI1	<---	Trialability_(TRI)	1.000				
CPX3	<---	Complexity_(CPX)	1.433	.250	5.725	***	par_8
CPX4	<---	Complexity_(CPX)	1.000				
MOT5	<---	Motivation_(MOT)	1.172	.067	17.399	***	par_9
MOT4	<---	Motivation_(MOT)	1.179	.064	18.324	***	par_10
RA3	<---	Relative_advantage_(RA)	1.030	.051	20.338	***	par_18
RA5	<---	Relative_advantage_(RA)	1.048	.049	21.480	***	par_19
TRN4	<---	Training_(TRN)	1.000				
OBS2	<---	Observability_(OBS)	1.000				

Table 5-29, Unidimensionality verification using a p-value of significance and C. R. value. Further to test the hypotheses related to the structural model the next step is taken was the test of unidimensionality which is expected to reveal whether a set of variables have only one underlying dimension in common (Janssens et al., 2008). For instance, Avcilar and Varinli (2013) explain unidimensionality signifies that observed variables used to measure each dimension must measure only one dimension. That is to say that the items retained in the final model to measure the latent constructs must indicate that the construct those items are measuring in reality measures that constructs and not any other. This is indicated by the p-value of significance produced by AMOS (<0.05 for acceptability), the critical ratio of each observed variable (>1.96) and the standardised regression weights of those items that measure the latent variable (>0.5) (Janssens et al.

2008). Table 5-29 provides the measurements concerning the p-value of significance and C, R. values as also the regression weights (table 5-30). The tabulations show that all observed variables meet the minimum requirements concerning p-value of significance, C.R. value and standardised regression weights thus indicating that the items used in the structural model exhibit unidimensionality.

Standardised Regression Weights: (Group number 1 - Default model)

Table 5-30: Unidimensionality measurement using the standardised regression weights

			Estimate
RA6	<---	Relative_advantage_(RA)	.852
MOT1	<---	Motivation_(MOT)	.761
TRN5	<---	Training_(TRN)	.937
OBS1	<---	Observability_(OBS)	.827
CI1	<---	Continuous_intention_(CI)	.805
CI2	<---	Continuous_intention_(CI)	.919
CI3	<---	Continuous_intention_(CI)	.826
CI4	<---	Continuous_intention_(CI)	.895
CMP2	<---	Compatibility_(CMP)	.655
CMP4	<---	Compatibility_(CMP)	.648
TRI2	<---	Trialability_(TRI)	.803
TRI1	<---	Trialability_(TRI)	.876
CPX3	<---	Complexity_(CPX)	.990
CPX4	<---	Complexity_(CPX)	.701
MOT5	<---	Motivation_(MOT)	.885
MOT4	<---	Motivation_(MOT)	.917
RA3	<---	Relative_advantage_(RA)	.869
RA5	<---	Relative_advantage_(RA)	.898
TRN4	<---	Training_(TRN)	.867
OBS2	<---	Observability_(OBS)	.644

Further to conducting the path analysis, the next test conducted was to check the presence of common method bias or common method variance in the data used for this research. Hair et al. (2017). Common method bias can arise in a survey conducted to collect data, due to self-reported measures from the same sample (Podsakoff & Todor, 1985). The presence of common method bias indicates the amount of spurious correlation that exists amongst the variables produced due to the usage of the same method (for instance survey) to measure each variable. One of the several methods used to determine the presence or absence of common method bias is Harman's single factor test (HSFT) (Tehseen et al., 2017). SPSS software provides the facility to conduct Harman's single factor test. In this test, all observable variables of every latent construct are loaded into a factor analysis to examine whether one single factor emerges and is accountable for not more than 50% of the variance in the data (Dhoopar et al., 2021; Chang et al., 2010). The results of the test generated by SPSS are presented in table 5-31.

Table 5-31: Results of the Harman's single factor test.

Total Variance Explained						
Factor	**Initial Eigenvalues**			**Extraction Sums of Squared Loadings**		
	Total	**% of Variance**	**Cumulative %**	**Total**	**% of Variance**	**Cumulative %**
1	18.732	39.025	39.025	18.170	37.853	37.853

From table 5-31 it can be seen that the factor analysis of all the items loaded for testing the common method variance has resulted in only one factor that explains variance of 37.853 percent in the data which is less than the acceptable 50% found in the relevant literature. Thus, it was concluded that common method variance or bias was absent in the data.

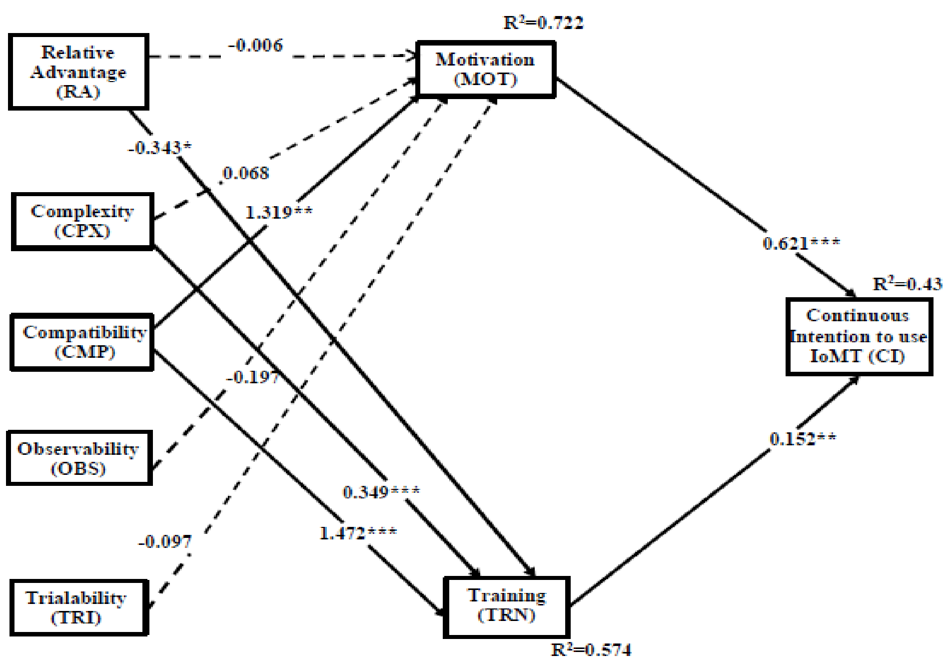


Figure 5.7: Fully tested structural model

At this stage, the data analysis with regard to the structural model was completed and the resulting model is depicted in figure 5.7. Further to this, the analysis of the influence of moderators on the structural model was analysed in the following sections.

5.14.4. Moderator analysis

In this section the hypotheses concerning the moderators will be tested. The hypotheses to be tested are listed in table 5-32.

Table 5-32:List of hypotheses concerning the moderators.

Hypotheses No.	Hypotheses statement
H8	Age moderates the relationship between motivation to use IoMT and continuous intention to use IoMT positively in older adults and negatively in younger people.
H9	Age moderates the relationship between motivation to use IoMT and continuous intention to use IoMT positively in older adults and negatively in younger people.
H10	Novelty seeking positively moderates the relationship between motivation to use IoMT and continuous intention to use IoMT.
H11	Novelty seeking positively moderates the relationship between training to use IoMT and continuous intention to use IoMT.
H12	Awareness of AI positively moderates the relationship between the relative advantage of IoMT and training in IoMT.
H13	Awareness in AI positively moderates the relationship between complexity in IoMT and training in IoMT.
H14	Awareness in AI positively moderates the relationship between compatibility in IoMT and training in IoMT.

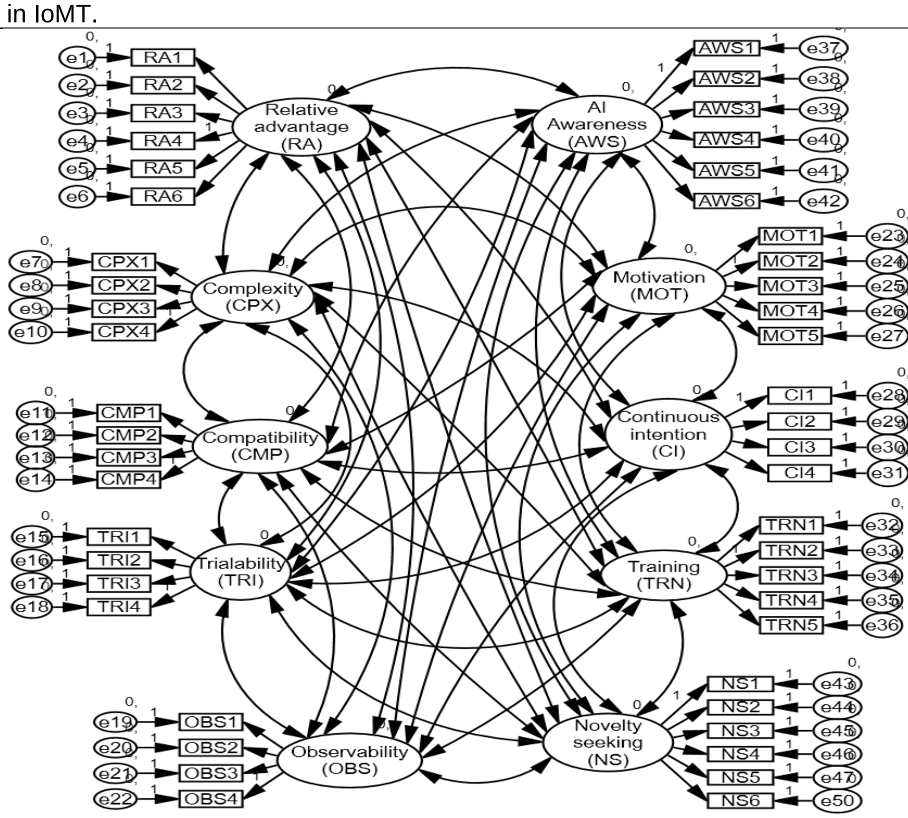


Figure 5.8: CFA model with the moderators.

The CFA model that included both the structural model factors in figure 5.8 and moderators namely artificial intelligence awareness (AWS) and novelty-seeking behaviour of healthcare professionals (NS) was the basis to analyse the moderation effect of the moderators on specific relationships identified in the research relationship model. The CFA model with the moderators is provided in figure 5.9. Age was not included in the CFA as it is a single item variable.

The CFA analysis was carried out on the model in figure 5.8 as per the steps given in section 4.12.2. The details of the analysis are provided in Appendix 12. The factorised model is given figure 5.9.

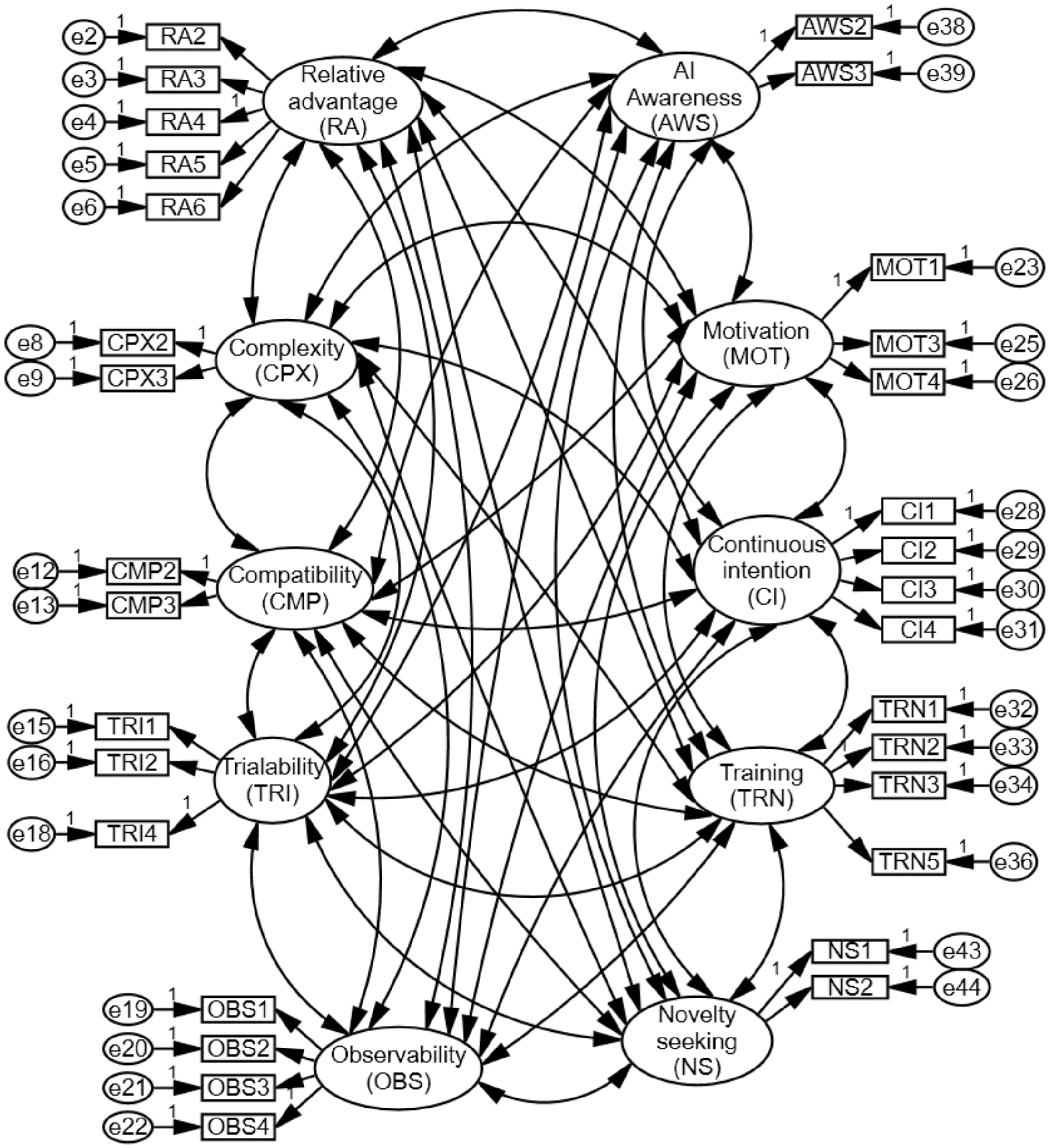


Figure 5.9: Factorised model with moderators.

The resulting factorized model showed that the final list of moderating items required to be analysed is provided in table 5-33.

Table 5-33:List of items used in measuring the moderators

#	Construct	Code	Items identified in the initial model	Items retained to measure the construct
1	Artificial intelligence awareness	AWS	AWS1-AWS6	AWS2 and AWS3
2	Novelty seeking behaviour	NS	NS1-NS6	NS1 and NS2
3	Age	Age1	Age1	Age1

Thus, the final model with the exogenous and endogenous constructs including the moderators is provided in figure 5.10.

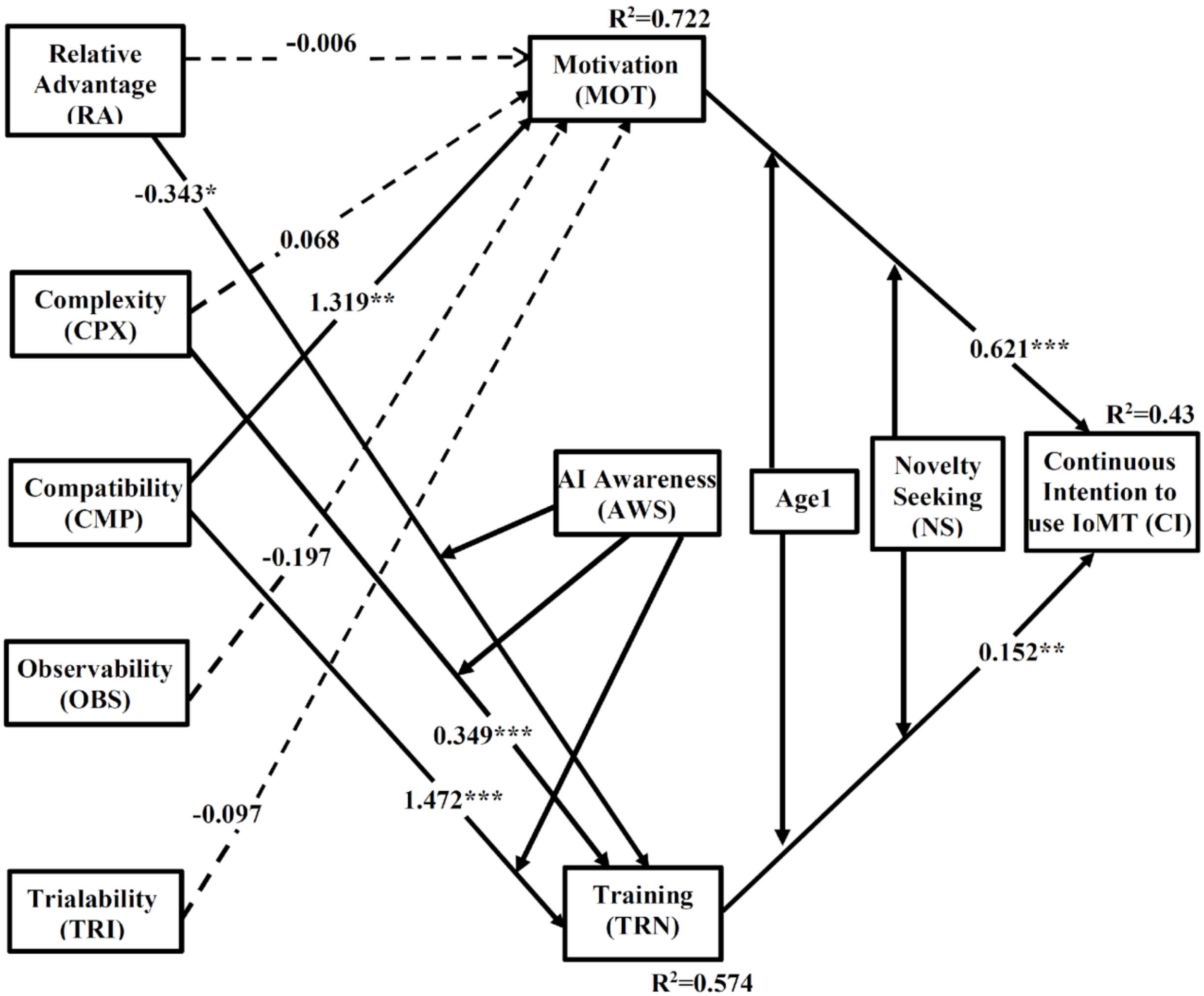


Figure 5.10: The structural model with moderator

From figure 5.10 it can be seen that AWS is shown to moderate the relationships (RA→TRN), (CPX→TRN) and (CMP→TRN), while NS and Age1 are shown to moderate the relationships (MOT→CI) and (TRN→CI). In the process of moderation, RA, CPX and CMP are the independent variables in their relationship with TRN whereas MOT and TRN are the independent variables in their relationship with CI. According to the literature, the test of moderation is carried out by regressing the dependent variable with the moderator, the independent variable and a multiplying factor. The moderating factor is the one which is the product of the independent and moderating variables. For example, in figure 5.10, AWS is tested for its moderating effect on the relationship (RA→TRN). The independent variable is RA. The moderating variable is TRN. The multiplication factor is (RA*AWS). Then the following regression equation can be written to test the moderating effect of AWS on the relationship (RA→TRN).

TRN = TRN1+TRN2+TRN3+TRN5 (From figure 5.9)

$TRN = [\beta_0 + (\beta_{RA})RA + (\beta_{AWS})AWS + (\beta_{RAAWS})\ (RA*AWS) + e_{mod}]$

$(TRN1+TRN2+TRN3+TRN5) = [\beta_0 + (\beta_{RA})RA + (\beta_{AWS})AWS + (\beta_{RAAWS})\ (RA*AWS) + e_{mod}]$

where:

TRN1, TRN2, TRN3 and TRN5 are items (figure 5.9) measuring the endogenous construct TRN.

β_0 = is the constant.

(β_{RA}) = coefficient of regression of RA.

(β_{AWS}) = coefficient of regression of AWS.

(β_{RAAWS}) = coefficient of regression of the product factor (RA*AWS).

e_{mod} = error component.

The main component involved in the product factor (RA*AWS). During the process of regression, if the product factor is found to have a p-value of significantly less than or equal to 0.05, then it will be concluded that there is a moderation effect on the relationship (RA→TRN) by AWS, else moderation is absent. It must be borne in mind that in this thesis the focus is to just test whether moderation occurs or not and the corresponding hypotheses. Knowledge about the effect of moderation is expected to help in an understanding of the factors that affect a particular relationship thus enabling the researcher to draw conclusions on the overall picture of the behaviour of the healthcare professionals in continuously using IoMT. From the above arguments, the other regression equations regarding the other moderators could be formulated. These are provided below.

$(TRN1+TRN2+TRN3+TRN5) = [\beta_1 + (\beta_{CPX})RA + (\beta_{AWS})AWS + (\beta_{CPXAWS})(CPX*AWS) + e_{mod1}]$

$(TRN1+TRN2+TRN3+TRN5) = [\beta_2 + (\beta_{CMP})RA + (\beta_{AWS})AWS + (\beta_{CMPAWS})(CMP*AWS) + e_{mod2}]$

CI=CI1+CI2+CI3+CI4 (from figure 5.9)

$(CI1+CI2+CI3+CI4) = [\beta_3 + (\beta_{MOT})MOT + (\beta_{NS})NS + (\beta_{MOTNS})(MOT*NS) + e_{mod3}]$

$(CI1+CI2+CI3+CI4) = [\beta_4 + (\beta_{MOT})MOT + (\beta_{AGE1})AGE1 + (\beta_{MOTAGE1})(MOT*AGE1) + e_{mod4}]$

$(CI1+CI2+CI3+CI4) = [\beta_5 + (\beta_{TRN})TRN + (\beta_{NS})NS + (\beta_{TRNNS})(TRN*NS) + e_{mod5}]$

$(CI1+CI2+CI3+CI4) = [\beta_6 + (\beta_{TRN})TRN + (\beta_{AGE1})NS + (\beta_{TRNAGE1})(TRN*AGE1) + e_{mod6}]$

The analysis of the moderators have been carried out based on the following procedure. The mean value of the items used to measure the construct's relative advantage, complexity, compatibility, motivation, training and continuous intention to use IoMT found in the tested and finalised structural model (figure 5.10) was taken and made into new variables in the SPSS. New codes were given using SPSS (see table 5-33). Similarly, the mean value of the items used to measure artificial intelligence awareness and novelty-seeking behaviour of healthcare professionals, provided in table 5-34, were taken and made into new variables in the SPSS. New codes were given to these variables using SPSS (see table 5-34). The product factors were arrived at by multiplying the relevant new variables derived out of the mean values mentioned above and then new variables pertaining to the product factors were derived using SPSS (see table 5-34).

Table 5-34: List of latent variables and moderators whose means have been computed

#	New constructs	Code	Explanation
1	Mean relative advantage	MeanRA356	Average of items RA3, RA5 and RA6
2	Mean complexity	MeanCPX34	Average of items CPX3 and CPX4
3	Mean compatibility	MeanCMP24	Average of items CMP2 and CNP4

4	Mean artificial intelligence	MeanAWS23	Average of items AWS1- AWS6
5	Mean motivation	MeanMOT145	Average of items MOT1, MOTand MOT5
6	Mean training	MeanTRN45	Average of items TRN4 and TRN5
7	Mean novelty seeking behaviour	MeanNS12	Average of items NS1-NS4 and NS6
8	Mean continuous intention to use	MeanCI	Average of items CI1-CI4
9	Age1	Age1	No average as Age1 was a single item variable
10	Product factor of RA-AWS	MULTIMEANRA356AWS23	(MeanRA356 * MeanAWS23)
11	Product factor of CPX-AWS	MULTIMEANCPX34AWS23	(MeanCPX34 * MeanAWS23)
12	Product factor of CMP-AWS	MULTIMEANCMP24AWS23	(MeanCMP24 * MeanAWS23)
13	Product factor of MOT-NS	MULTIMEANMOT145NS12	(MeanMOT145 * MeanNS12)
15	Product factor of TRN-NS	MULTIMEANTRN45NS12	(MeanTRN45 * MeanNS12)
16	Product factor of MOT-Age	MULTIMEANMOT145AGE1	(MeanMOT145 * Age1)
17	Product factor of TRN-Age	MULTIMEANTRN45AGE1	(MeanTRN45 * Age1)

AMOS was used to test the moderation effect of the moderators Age1, NS and AWS.

Moderation of (MOT-CI) relationship by Age1

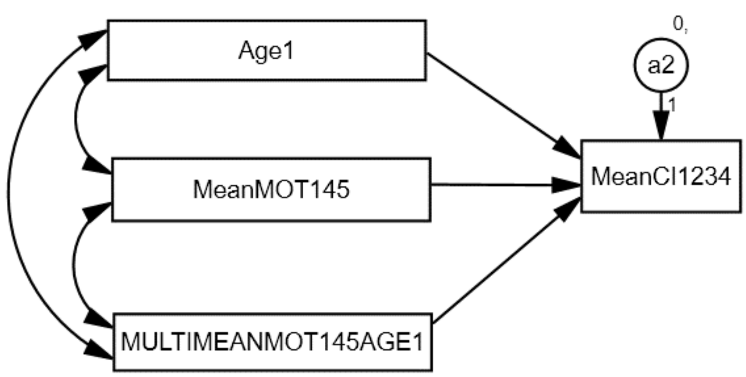


Figure 5.11: AMOS model used to test the moderation of the relationship MOT-CI by Age1.

The result of analysing the model in figure 5.11 using AMOS is provided in table 5-35.

Regression Weights: (Group number 1 - Default model)

Table 5-35: AMOS report on the moderation of the relationship MOT-CI by Age1.

			Estimate		S.E.	C.R.	P	Label
MeanCI1234	<---	Age1	.216		.146	1.473	.141	par_1
MeanCI1234	<---	MeanMOT145	.767		.121	6.360	***	par_2
MeanCI1234	<---	MULTIMEANMOT145AGE1	-.075		.040	-1.890	.059	par_3

From table 5-35 it can be seen that the product factor MULTIMEANMOT145AGE1 has not having a statistically significant relationship (p-value of significance 0.059 which is > 0.05) with the latent variable MeanCI1234. This implies that Age1 does not moderate the relationship between MOT and CI. Thus, it can be inferred that hypothesis H8 is not supported.

Moderation of (TRN-CI) relationship by Age1

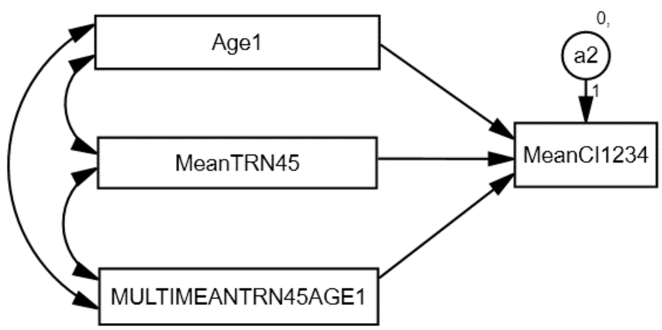


Figure 5.12: AMOS model used to test the moderation of the relationship TRN-CI by Age1

The result of analysing the model in figure 5.12 using AMOS is provided in table 5-36.

Regression Weights: (Group number 1 - Default model)

Table 5-36: AMOS report on the moderation of the relationship TRN-CI by Age1.

			Estimate	S.E.	C.R.	P	Label
MeanCI1234	<---	Age1	-.085	.125	-.679	.497	par_1
MeanCI1234	<---	MULTIMEANTRN45AGE1	.006	.037	.171	.865	par_2
MeanCI1234	<---	MeanTRN45	.366	.114	3.226	.001	par_6

From table 5-36 it can be seen that the product factor MULTIMEANTRN45AGE1 is not having a statistically significant relationship (p-value of significance 0.865 which is > 0.05) with the latent variable MeanCI1234. This implies that Age1 does not moderate the relationship between TRN and CI. Thus, it can be inferred that hypothesis H9 is not supported.

Testing the hypotheses concerning moderator Age1

H8: Age moderates the relationship between motivation to use IoMT and continuous intention to use IoMT positively in older adults and negatively in younger people.

H9: Age moderates the relationship between motivation to use IoMT and continuous intention to use IoMT positively in older adults and negatively in younger people.

Age as a demographic factor has been suggested for use in both theoretical models (e.g., UTAUT) (Venkatesh et al., 2013) and other empirical research work (e.g., Rajmohan & Johar, 2020) as a moderator. Consistent with these arguments in this research age was included to know whether it moderates the relationships (MOT-CI) and (TRN-CI). Results show that age does not moderate these two relationships. This result can be interpreted in a way that continuous intention to use IoMT is not age-related as motivation to use and training in IoMT are considered to be age-independent in the extant literature. For instance, Nikolopoulou et al. (2021) did not find any impact of age as a moderator in their research on teachers' intention to use mobile internet using the UTAUT model which includes hedonic motivation and facilitating conditions (Venkatesh et al., 2003). Similar results were reported by other researchers including Kousloglou et al. (2021). Thus, the results of this research can be seen to be in line with the already published results in the literature. These results imply that continuous intention to use is influenced by both motivation and training to use IoMT, but those relationships are not affected by the age of the healthcare professionals. The above discussions clearly show why and how hypotheses H8 and H9 are rejected and evaluated using extant literature.

Moderation of (MOT-CI) relationship by NS

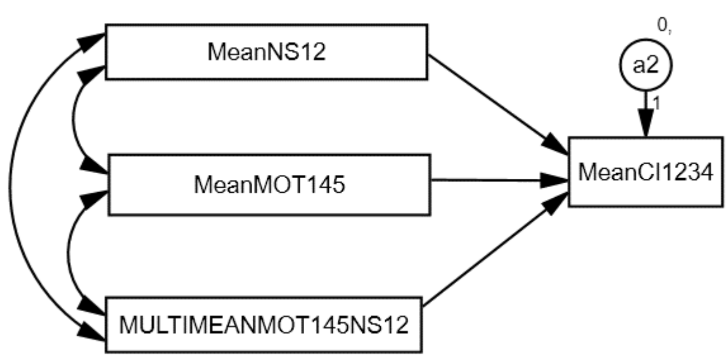


Figure 5.13: AMOS model used to test the moderation of the relationship MOT-CI by NS.

The result of analysing the model in figure 5.13 using AMOS is provided in table 5-37.

Regression Weights: (Group number 1 - Default model)

Table 5-37: AMOS report on the moderation of the relationship MOT-CI by NS.

			Estimate	S.E.	C.R.	P	Label
MeanCI1234	<---	MeanNS12	.099	.128	.776	.438	par_1
MeanCI1234	<---	MeanMOT145	.441	.101	4.376	***	par_2
MeanCI1234	<---	MULTIMEANMOT145NS12	.011	.033	.340	.734	par_3

From table 5-37 it can be seen that the product factor MULTIMEANMOT145NS12 is not having a statistically significant relationship (p-value of significance 0.734 which is > 0.05) with the latent variable MeanCI1234. This implies that NS does not moderate the relationship between MOT and CI. Thus, it can be inferred that hypothesis H10 is not supported.

Moderation of (TRN-CI) relationship by NS

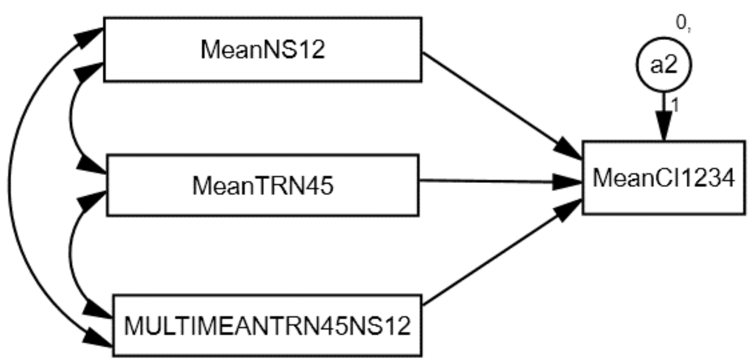


Figure 5.14: AMOS model used to test the moderation of the relationship TRN-CI by NS.

The result of analysing the model in figure 5.14 using AMOS is provided in table 5-38.

Regression Weights: (Group number 1 - Default model)

Table 5-38:AMOS report on the moderation of the relationship TRN-CI by NS.

			Estimate	S.E.	C.R.	P	Label
MeanCI1234	<---	MeanNS12	.393	.110	3.580	***	par_1
MeanCI1234	<---	MULTIMEANTRN45NS12	-.050	.033	-1.519	.129	par_2
MeanCI1234	<---	MeanTRN45	.403	.114	3.539	***	par_6

From table 5-38 it can be seen that the product factor MULTIMEANTRN45NS12 is not having a statistically significant relationship (p-value of significance 0.865 which is > 0.05) with the latent variable MeanCI1234. This implies that NS does not moderate the relationship between TRN and CI. Thus, it can be inferred that hypothesis H11 is not supported.

Testing the hypotheses concerning moderator novelty-seeking behaviour

H10 Novelty seeking positively moderates the relationship between motivation to use IoMT and continuous intention to use IoMT.

H11 Novelty seeking positively moderates the relationship between training to use IoMT and continuous intention to use IoMT.

The results concerning the moderation effect of novelty-seeking behaviour of healthcare professionals show that NS does not influence the relationships (MOT-CI) and (TRN-CI). Novelty seeking behaviour is linked to experience in the UTAUT model by Venkatesh et al. (2012). In fact, Venkatesh et al. (2012) argue that novelty seeking is expected to moderate the relationships (hedonic motivation-use behaviour) and (facilitating conditions-use behaviour). However, mixed results are found in the literature with regard to the moderating effect of novelty-seeking behaviour. For instance, in their research Schukat & Heise (2021) did not find any moderation by work experience on the relationship between hedonic motivation and facilitating condition on the one hand and use behaviour on the other. Similar results were derived by Dionika et al. (2019). Thus, the results of this research are in line with those researchers who found that novelty-seeking behaviour does not moderate the relationships (hedonic motivation-use behaviour) and (facilitating conditions-use behaviour). The above discussions clearly show why and how hypotheses H10 and H11 are rejected and evaluated using extant literature.

Moderation of (RA-TRN) relationship by AWS

Figure 5.15 provides the image of the models analysed using AMOS.

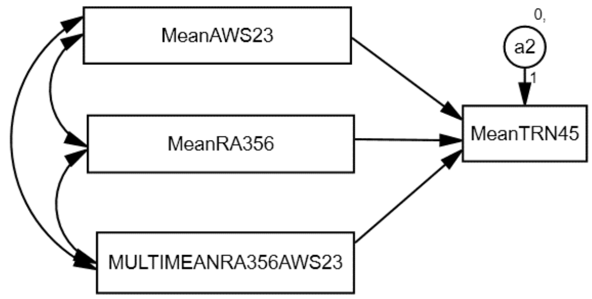


Figure 5.15: AMOS model used to test the moderation of the relationship RA-TRN by AWS.

The result of analysing the model in figure 5.15 using AMOS is provided in table 5-39.

Regression Weights: (Group number 1 - Default model)

Table 5-39: AMOS report on the moderation of the relationship RA-TRN by AWS.

			Estimate	S.E.	C.R.	P	Label
MeanTRN45	<---	MeanAWS23	.821	.123	6.700	***	par_1
MeanTRN45	<---	MeanRA356	.400	.096	4.155	***	par_2
MeanTRN45	<---	MULTIMEANRA356AWS23	-.072	.032	-2.231	.026	par_3

From table 5-39 it can be seen that the product factor MULTIMEANRA356AWS23 is having a statistically significant relationship (p-value of significance 0.026 which is less than ≤ 0.05) with the latent variable MeanTRN45. This implies that AWS is acting as a moderator of the relationship between RA and TRN. Thus, it can be inferred that hypothesis H12 is supported.

Moderation of (CPX-TRN) relationship by AWS

Figure 5.16 provides the image of the models analysed using AMOS.

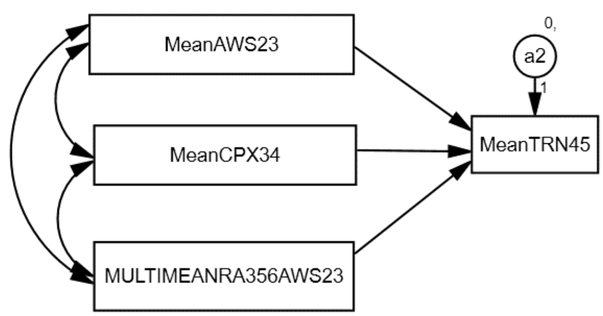


Figure 5.16: AMOS model used to test the moderation of the relationship CPX-TRN by AWS

The result of analysing the model in figure 5.16 using AMOS is provided in table 5-40.

Regression Weights: (Group number 1 - Default model)

Table 5-40: AMOS report on the moderation of the relationship CPX-TRN by AWS.

			Estimate	S.E.	C.R.	P	Label
MeanTRN45	<---	MeanAWS23	.816	.098	8.341	***	par_1
MeanTRN45	<---	MeanCPX34	.328	.107	3.076	.002	par_2
MeanTRN45	<---	MULTIMEANCPX34AWS23	-.074	.033	-2.213	.027	par_3

From table 5-40 it can be seen that the product factor MULTIMEANCPX34AWS23 is having a statistically significant relationship (p-value of significance 0.027 which is less than ≤ 0.05) with the latent variable MeanTRN45. This implies that AWS is acting as a moderator of the relationship between CPX and TRN. Thus, it can be inferred that hypothesis H13 is supported.

Moderation of (CMP-TRN) relationship by AWS

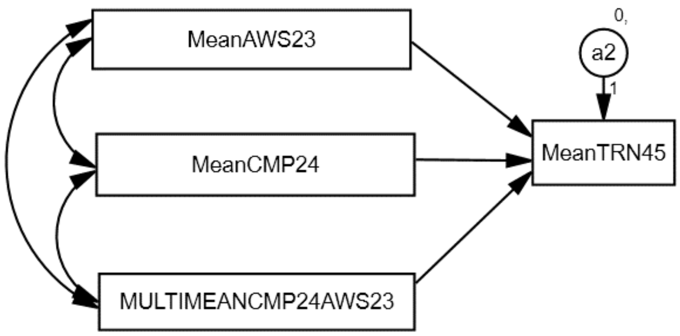


Figure 5.17: AMOS model used to test the moderation of the relationship CMP-TRN by AWS.

The result of analysing the model in figure 5.17 using AMOS is provided in table 5-41.

Regression Weights: (Group number 1 - Default model)

Table 5-41: AMOS report on the moderation of the relationship CMP-TRN by AWS.

			Estimate	S.E.	C.R.	P	Label
MeanTRN45	<---	MeanAWS23	.697	.126	5.541	***	par_1
MeanTRN45	<---	MeanCMP24	.349	.109	3.209	.001	par_2
MeanTRN45	<---	MULTIMEANCMP24AWS23	-.040	.035	-1.135	.256	par_3

From table 5-41 it can be seen that the product factor MULTIMEANCMP24AWS23 is not having a statistically significant relationship (p-value of significance 0.256 which is > 0.05) with the latent variable MeanTRN45. This implies that AWS does not moderate the relationship between CMP and TRN. Thus, it can be inferred that hypothesis H14 is not supported.

Testing of hypotheses concerning the moderator artificial intelligence awareness

H12: Awareness about AI positively moderates the relationship between the relative advantage of IoMT and training in IoMT.

H13: Awareness in AI positively moderates the relationship between complexity in IoMT and training in IoMT.

H14: Awareness in AI positively moderates the relationship between compatibility in IoMT and training in IoMT.

It can be interpreted that AWS moderates the RA-TRN and CPX-TRN relationships negatively with regression weights (-0.072) and (-0.074) respectively reported by AMOS for the product terms (see tables 5.36 and 5.37). Since the p-value of significance is less than 0.05, moderation was found. In practical terms, it can be inferred that when IoMT devices with technologies like AI embedded in them could be a challenge. Early adopters could find difficulty in using those devices. For instance, Fitbit Aria (Fitbit, 2020) is an IoMT tracking device and is a fitness wristband that is used in calculating the basal metabolic rate (BMR), which helps determine the estimated calorie expenditure of a person. This device needs to be used in sync with a tracking device like a mobile or a computer (Fitbit, 2020). Fitbit is a company dealing with IoMT devices. Fitbit uses AI technology in wearables. The technology could be initially a problem for healthcare professionals to understand and use. Such behaviour with regard to artificial intelligence or other technologies have been reported in the literature. For instance, Guerra (2018) argues that the power available to the users of AI influences the people to develop positive or negative emotional connections. Expressing similar sentiments Khakurel et al. (2018) argue that AI not only creates opportunities but also risks to sustainability. These arguments clearly show that the findings of this research are confirming the fears of some of the researchers about the usefulness of AI-based IoMT devices to healthcare professionals and their possible impact on their continuous intention to use IoMT. The results of this research show that relationship relative advantage of IoMT and its linkage to training in IoMT is negatively influenced by AWS. This finding is found to support the earlier finding of this research (reported in table 5-42), where it is shown that relative advantage negatively influences training in IoMT. This is a new finding not found in the literature concerning the diffusion of IoMT embedded with AI. That is to say that the higher the relative advantage of using IoMT lower will be the requirement of training and lower the relative advantage of using IoMT higher will be the training required. This situation prevails perhaps due to the negative influence caused by embedding AI in IoMT that might have led the respondents to feel that it is not easy to use such devices and hence the relative advantage is low. These results show that if this aspect is not addressed during the diffusion of IoMT, then there could be the sustainability of the continuous use of IoMT devices by healthcare professionals.

The foregoing discussions clearly show why and how hypotheses H12 and H13 are supported and evaluated using extant literature. Furthermore, the results of moderation (Appendix 12) that AWS does not moderate the relationship CMP-TRN with the product factor was found to have a p-value greater than 0.05. While literature (Almansoori et al., 2021) suggests that AWS can be used as a moderator in adoption research, compatibility of AI to users appears to be less of a concern. For instance, reporting the results of their study, Ream et al. (2018) argue compatibility problems (e.g., interoperability) related to AI are reduced to data compatibility issues and need to be overcome using labelling and standardisation. These arguments indicate that the influence of AWS on the relationship (CMP-TRN) may not be significant as it could be largely taken care of by appropriate technological tools. The results of this research thus confirm that lack of moderation of the relationship (CMP-TRN) by AWS is in line with the literature and practice. The above discussions clearly show why and how hypothesis H14 is rejected and evaluated using extant literature. The final model is provided in figure 5.18.

Further, from the results concerning the moderators, it can be seen that age was not found to be correlated with any of the constructs, namely motivation to use IoMT, training to use IoMT and continuous intention to use IoMT. This could be because a technology that is diffusing and dynamic in nature may not affect IoMT usage. The reason for this could be that most of the respondents who participated in this research (60.4%) were between 26 and 41 years old. This category of users may be using the internet of things as an inseparable part of their professional requirement and hence results indicate that continuous usage of IoMT needs to be delinked as a construct that can moderate the relationships between motivation to use IoMT, training to use IoMT and continuous intention to use IoMT. Similar results are reported by others in the literature (Cabeza-

Ramírez et al., 2020; Rajmohan and Johar, 2020) confirming that the current research outcomes are in line with others' findings.

Novelty-seeking behaviour of healthcare professionals was also found to not be moderating the relationships between motivation to use IoMT, training to use IoMT and continuous intention to use IoMT. The reason for this could be that IoMT is a diffusing technology that is evolving with the developments taking place in the field of the internet, the internet of things and IoMT. So, users might have felt IoMT as an extension of IOT and hence might not have felt IoMT as a novelty. Similar findings have also been reported by other researchers (Streukens and Andreassen, 2013; Hsiao et al., 2010) confirming the research outcomes of this research. Another reason for the lack of significance of novelty-seeking behaviour could be that compatibility was perhaps considered more important than the novelty attribute of a diffusing technology. This highlights a fundamental cultural need to allow technology to drive organisational and process change. Thus, the result derived in this research indicating that novelty-seeking behaviour is not a significant moderator shows that where users are interested more in the compatibility of technology rather than novelty in such environments, continuous intention to use IoMT is more likely. This is an important finding of this research.

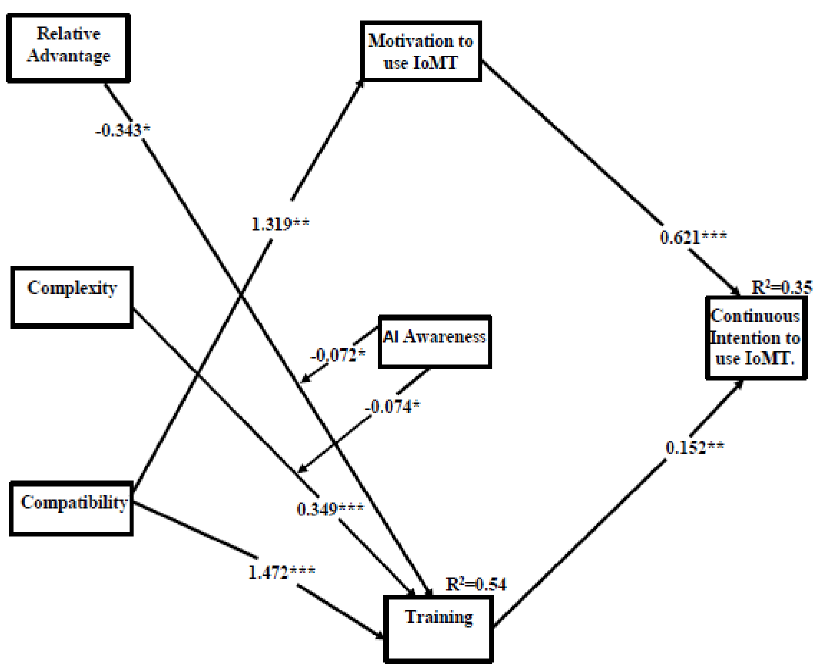


Figure 5.18: Finally tested model with independent, dependent, mediating and moderating variables.

The final list of hypotheses supported and rejected is provided in table 5-42.

Table 5-42: Final list of supported and rejected hypotheses.

Hypotheses No.	Hypotheses statement	Supported/ rejected
H1a	Relative advantage of IoMT positively influences the motivation of users to use IoMT.	Rejected
H1b	Relative advantage of IoMT positively influences training to use IoMT.	Supported
H2a	Complexity of IoMT influences negatively motivation to use IoMT.	Rejected
H2b	Complexity of IoMT positively influences training in IoMT.	Supported
H3a	Compatibility of IoMT positively influences motivation to use IoMT.	Supported
H3b	Compatibility of IoMT positively influences training to use IoMT.	Supported
H4	Observability of IoMT positively influences Motivation of IoMT,	Rejected
H5	Trialability of IoMT positively influences motivation to use IoMT,	Rejected
H6	Motivation to use IoMT positively influences continuous intention to use IoMT.	Supported
H7	Training in IoMT positively influences continuous intention to use IoMT.	Supported
H8	Age moderates the relationship between motivation to use IoMT and continuous intention to use IoMT positively in older adults and negatively in younger people.	Rejected
H9	Age moderates the relationship between motivation to use IoMT and continuous intention to use IoMT positively in older adults and negatively in younger people.	Rejected
H10	Novelty seeking positively moderates the relationship between motivation to use IoMT and continuous intention to use IoMT.	Rejected
H11	Novelty seeking positively moderates the relationship between training to use IoMT and continuous intention to use IoMT.	Rejected
H12	Awareness about AI negatively moderates the relationship between the relative advantage of IoMT and training in IoMT.	Supported
H13	Awareness in AI negatively moderates the relationship between complexity in IoMT and training in IoMT.	Supported
H14	Awareness in AI negatively moderates the relationship between compatibility in IoMT and training in IoMT.	Rejected

5.15. Chapter summary

This chapter has provided a detailed data analysis using the data collected to test the research model. The results show that the data and the research instrument are reliable and valid. In addition, path analysis showed that motivation is a weak mediator while training to use IoMT adds to the determining power of the model. All the exogenous variables indirectly contributed to the determination of the dependent namely continuous intention to use IoMT. Amongst the exogenous variables RA, CPX and CMP were shown to determine CI while training to use IoMT was found to be a strong mediator. Motivation was not found to be a strong mediator. As far as the moderators were concerned, it can be seen that only AWS was shown to moderate two relationships namely (RA-TRN) and (CPX-TRN). Thus, the outcome of this chapter is now ready to be discussed in the next chapter.

6. Chapter 6: Discussion

6.1. Introduction

This chapter is about the new findings the research has come up with that contribute to the existing body of knowledge concerning the central issue of determining the continuous intention of the healthcare professionals to use IoMT influenced by the diffusion of innovation factors and moderators. In this chapter, the findings derived from the data analysis in chapter 5 will be discussed. In the beginning the effect of the determinants on continuous intention to use IoMT will be discussed using the total, direct and indirect effects of those determinants on continuous intention to use IoMT. The outcome of the discussions is then related to the hypotheses tested in chapter 5 and inferences will be derived by answering the research questions. The answers have been then compared with the extant literature to identify the new findings of this research.

6.2. Discussions on the direct and indirect effect of the relationships amongst latent variables

The statistical analysis of the various paths representing the relationships amongst the latent variables as depicted in the research model in chapter 3 provide clues to understanding the determinants of the diffusion of IoMT as an innovation embedded with artificial intelligence. This analysis was also used to answer research question RQ1 and provide an idea about the additions this research makes to the body of knowledge concerning the diffusion of IoMT and the intention of the healthcare professionals to continuously use IoMT. The AMOS results (tables 6.1 & 6.2) concerning the standardised direct and indirect effects of the exogenous variables on endogenous variables were analysed, to begin with followed by the total effect (Arbuckle, 2019). The results are given in table 6-1.

6.3. Direct effect

Table 6-1: Direct effect of determinants on mediators and mediators on dependent variables.

	Complexity (CPX)	Trialability (TRI)	Compatibility (CMP)	Observability (OBS)	Relative advantage_(RA)	Training (TRN)	Motivation (MOT)	Continuous intention_(CI)
Training_(TRN)	.349	.000	1.472	.000	-.343	.000	.000	.000
Motivation_(MOT)	.068	-.097	1.319	-.197	-.006	.000	.000	.000
Continuous intention_(CI)	.000	.000	.000	.000	.000	.152	.621	.000

Table 6-2: Indirect effect of the determinants on mediators and dependent variables.

	Complexity_(CPX)	Trialability_(TRI)	Compatibility_(CMP)	Observability_(OBS)	Relative_advantage_(RA)	Training_(TRN)	Motivation_(MOT)	Continuous_intention_(CI)
Training_(TRN)	.000	.000	.000	.000	.000	.000	.000	.000
Motivation_(MOT)	.000	.000	.000	.000	.000	.000	.000	.000
Continuous_intention_(CI)	.095	-.060	1.043	-.122	-.056	.000	.000	.000

From the table 6-1 it can be seen that the exogenous variables namely relative advantage, complexity, compatibility, trialability and observability have different effects on the mediators. This table needs to be read in conjunction with table 6-3 reproduced below for convenience.

Standardised Regression Weights: (Group number 1 - Default model)

Table 6-3: Standardised regression weights of the relationship between the exogenous variables and CI.

			Estimate	P-Value
Motivation_(MOT)	<---	Relative_advantage_(RA)	-.007	.977
Motivation_(MOT)	<---	Compatibility_(CMP)	1.036	.004
Motivation_(MOT)	<---	Trialability_(TRI)	-.120	.344
Motivation_(MOT)	<---	Complexity_(CPX)	.062	.349
Training_(TRN)	<---	Complexity_(CPX)	.268	***
Motivation_(MOT)	<---	Observability_(OBS)	-.174	.195
Training_(TRN)	<---	Relative_advantage_(RA)	-.330	.048
Training_(TRN)	<---	Compatibility_(CMP)	.967	***
Continuous_intention_(CI)	<---	Training_(TRN)	.162	.006
Continuous_intention_(CI)	<---	Motivation_(MOT)	.552	***

It can be seen from Table 6-3 that the direct paths RA→MOT, CPX→MOT, TRI→MOT and OBS→MOT have been found to be insignificant. Hence these paths will not be discussed. However, the other paths namely RA→TRA, CMP→MOT, CMP→TRA, CPX→TRA, TRA→CI and MOT→CI are significant, and the implications of this finding are discussed next.

6.3.1. The direct effect of the exogenous variables on motivation to use IoMT

This subsection explains five hypotheses H1a, H2a, H3a, H4a and H5a.

Hypotheses H1a: Relative advantage of IoMT positively influences motivation to use IoMT

Hypotheses H2a: Complexity of IoMT positively influences motivation to use IoMT

Hypotheses H3a: Compatibility of IoMT positively influences motivation to use IoMT

Hypotheses H4: Trialability of IoMT positively influences motivation to use IoMT

Hypotheses H5: Observability of IoMT positively influences motivation to use IoMT

From table 6-3 it is seen that the only exogenous variable that has a direct effect on motivation is compatibility. Out of the five exogenous variables that have been identified in the research model (see figure 3.7) only compatibility had a statistically significant effect on motivation that is direct and positive. This implies that during the process of diffusion of IoMT, there is no influence of relative advantage, complexity, trialability and observability on the motivation of the professionals to continuously use IoMT. However, literature shows that the results obtained by other researchers in similar research areas have produced mixed results. For instance, Jilani et al., (2022) used a small to medium correlation between motivation and the five variables of DoI. However, Wang (2022), while finding a statistically significant relationship between motivation, relative advantage, complexity and compatibility, did not find a statistically significant relationship between trialability and observability.

The reason for this could be for many reasons. For instance, when innovation is having a high relative advantage and low complexity then adoption intention appears to be a direct result without the need for an intervention like motivation. Examples of research outcomes where researchers have directly linked DoI factors to intention to adopt or continuous intention to use technology are found in the literature (e.g., Giglio & De Mai, 2022; Lubis et al., 2019). Another reason could be that motivation is considered to be a moderator and not a mediator of the relationship between DoI factors and continuous intention to use (e.g., Jilani et al., 2022). A third reason could be that integrating diffusion of innovation factors with behavioural factors could be complex. For instance, Zubair et al. (2021) argue that work motivation is a complex subject which implies that the interrelationship between DoI factors and motivation could be a complex issue and hence under-researched. The above arguments show that the relationship between DoI factors and motivation is not well researched and in exceptional cases produced mixed results. Thus, on one side, there is no well-established relationship between DoI factors and motivation to use IoMT while on the other there are sporadic papers that have related motivation to DoI constructs as moderators. Thus, research that has attempted to link diffusion factors and behavioural factors like motivation is sparse. Considering the above-mentioned aspects, it is possible to explain the lack of statistical significance of the four relationships namely relative advantage → motivation, complexity → motivation, trialability → motivation and observability → motivation. However, the reason why there was a statistically significant relationship between compatibility → motivation needs explanation which is provided in the next paragraph. Based on the abovementioned arguments it can be concluded that the rejection of the hypotheses H1a, H1b, H1d and H1e is valid.

Explanation of supporting hypothesis H3a: Compatibility of IoMT positively influences motivation to use IoMT.

From table 6-1 it can be seen that compatibility has a direct effect of 1.319 on motivation in the positive direction. This implies that a one standard deviation change incompatibility is expected to produce a change of 1.3 standard deviations on motivation. The interpretation is that when the compatibility of IoMT during diffusion changes in the positive direction, then the motivation of the healthcare professionals' changes in the positive direction and vice versa. In practical terms change the incompatibility of IoMT can be explained using the items used to measure compatibility. For instance, one of the items (CMP2) used to measure compatibility reads as "Using an IoMT is completely compatible with my current situation". The mean of the responses obtained for CMP2 stands at 3.2 (see table 6-4).

Table 6-4: Mean of the responses to the item CMP2.

Statistics		
Using an IoMT is completely compatible with my current situation.		
N	Valid	354
	Missing	0
Mean		3.2401
Std. Deviation		1.07849
Minimum		1.00
Maximum		5.00

If the situation in the healthcare sector related to IoMT changes due to a change in technology, then there is every possibility that the response of the user changes. For instance, in the current example if the mean of the responses obtained against the item CMP2 changes from 3.2 to 4.2 (which is the point representing the response 'agree' from being 'neutral' on the Likert scale and is equal to one standard deviation), that is in the positive direction, then the motivation of the respondents could change in the positive direction by 1.3 standard deviations. That is to say, the motivation of the healthcare professionals to continuously use IoMT could increase to an extent higher than the change seen incompatibility. This is an important finding. Similar findings have not been found in the literature reported by other researchers in the context of IoMT although there are research findings similar to this in other fields. For instance, Liao et al. (2021) found a positive relationship between compatibility and intrinsic and extrinsic motivation in their study on improving users' loyalty to smart health devices viewed from the perspective of compatibility. Similarly, Zogheib (2019) found a positive relationship between perceived compatibility and attitude of students in the investigation of the influence of perceived usefulness and perceived compatibility on students' attitudes towards using an iPad. Attitude is used in behavioural literature as a synonym for motivation. For instance, Ryan (2000; p. 54) claims that "orientation of motivation concerns the underlying attitudes and goals that give rise to action- that is, it concerns the why of actions". Similar sentiments are echoed by Khalid (2016). Thus, this research is adding to the body of knowledge with regard to the continuous intention to use IoMT.

Furthermore, another finding that adds to the body of knowledge is the high predictive power of compatibility, which shows that a one standard deviation change incompatibility results in approximately 1.3 standard deviations change in motivation. That is to say that when practitioners of IoMT find compatibility of IoMT to their requirements, then they are highly motivated although it is difficult to determine the level of such motivation numerically. Thus, manufacturers of IoMT need to ensure that the compatibility of IoMT devices and related equipment with the users must be high so that users find it motivating and develop a liking to continuously use the devices and equipment. During the diffusion of IoMT where different types of users will be introduced to IoMT, compatibility of IoMT to users appears to be the single most important construct that will determine the continuous intention to use IoMT as the other four diffusions of innovation factors namely relative advantage, complexity, trialability and observability did not have any effect on motivation. In a way, this result shows that the application of diffusion of innovation theory is only partially explaining the impact of the diffusion factors on the motivation of healthcare professionals. That is to say during the diffusion of IoMT and the channel through which the communication about IoMT spreads, before the users accept, adopt and use IoMT, it is the compatibility of IoMT that the users are looking for the most. This implies that the remaining four diffusions of innovation factors namely relative advantage, complexity, trialability and observability are not significant in motivating the users of IoMT when IoMT is still diffusing. One of the reasons for this could be that participants in the research would have felt that IoMT being a new innovation, would have built-in features that provide advantages relative to the traditional methods used in providing healthcare and are easy to use with little complexity, without trialability and observability. This is another new finding as most researchers have used and recommended more than one diffusion of innovation factor in their research concerning the usage of the innovation (Mabad et al., 2021; Salleh & Daud, 2019; Yoo & Kim, 2018). This research contradicts this assumption although there have been rare publications found in the literature that have used a single diffusion component to determine usage or continuous usage of innovation but not in the area of IoMT, for instance, Zogheib (2019) used compatibility only as a diffusion factor while investigating the influence of perceived usefulness and perceived compatibility on students’ attitudes towards using iPad.

In practical terms, it is possible to interpret this result as follows. When the level of compatibility of IoMT to user needs is said to be high, it may imply that the IoMT devices are ready to use for instance as a plugin without the need to get trained in the usage of the device or spend hours together to learn how to use the device and the technology is very easy to use. In such a situation it is possible that the relative advantage of using IoMT is high, complexity is less and there is no need for trialability and observability of IoMT during diffusion and before accepting the technology for use. With the pace at which technology is advancing and being used in IoMT devices, it is perhaps reasonable that healthcare professionals expect a situation in which except for the compatibility of IoMT, the rest of the factors described by DoI theory, that is a relative advantage, complexity, trialability and observability, should not matter if those professionals intend to use IoMT. This is a new finding and to the knowledge of the researcher, similar findings to this effect are not found in the IoMT literature concerning the intention to use IoMT. Based on the foregoing explanations, it is possible to conclude that hypothesis H3a can be supported.

6.3.2. The direct effect of relative advantage on training in IoMT

This section addresses hypothesis H1b which states, *"Relative advantage of IoMT positively influences training to use IoMT"*.

Training is an essential part of any diffusing technology and the relative benefit of innovation like IMoT will remain underutilised if training is absent. Poggensee and Collins (2021; p. eabf1078) aptly said "we do not know the relative importance of training, how much is required, or what type is most effective; how people adapt with the device; or the relative benefits of customizing assistance". Thus, it can be seen that training happens to be an area that needs greater understanding, especially with regard to relative benefits.

From table 6-1, it can be seen that relative advantage has a direct effect on training to use IoMT. The AMOS report (see table 6-1) shows that the direct effect of relative advantage on training is -0.343. This implies that when there is a one standard deviation change in the relative advantage of IoMT in the positive direction, then the training requirement to use IoMT changes by 0.343 standard deviations in the negative direction. This result can be expected as technological advances must enhance the relative advantage of IoMT and make the application of IoMT devices easy thus reducing the need for training in IoMT. For example, the technology behind some of the wearables that have come into the market is easy to use and wear on the wrist like a wristwatch, and such devices monitor blood pressure and act as fitness trackers (Healthline, 2021). These wristwatches based on advanced technology require minimum training as the manufacturers ensure that common people including both the patient and the physician can use them with very little training and are ready to use. Such watches are now common accepted in part due to simplicity of use.

The results of this research with regard to the relationship between relative advantage and training gain support from real-life happenings. These results find support in the relevant literature. For instance, Rago and Zucchi (2020) found through their research on the personal characteristics of physicians that influence the adoption of innovations that minimum training was enough for the physicians to understand the relative advantage and compatibility of wearables. The researchers found that while training is necessary, the length of training was not relevant, and more sessions did not lead to a better understanding of the relative advantage or compatibility of medical devices in physicians. Thus, the outcomes of this research bring out an important fact that the greater the relative advantage less important will be the training requirement. With the exception of the research conducted by a few researchers Rago and Zucchi (2020), hardly any research outcomes have been found that have related relative advantage to training in the context of IoMT during the process of diffusion. It is important to realise here that although the statement that relative advantage is linked to training negatively which appear to be common knowledge, during the process of diffusion of innovation, it is not easy to determine how the technology will affect the users and their needs, which makes the training aspect unpredictable. In fact, in such situations determining training requirements as inversely related to the relative advantage of a device cannot be an automatic happening. With rapidly changing technology and shorter time is taken to diffuse, it is important to understand the training requirements of the users, failing which the successful use of a device by the users could not be determined. This is an important contribution to knowledge as most often researchers argue that the higher the training greater the perceived relative advantage of an innovation (Mairura, 2016; Lee et al., 2011). From the foregoing discussions, it can be seen hypothesis H1b stands supported and the explanation behind it.

6.3.3. The direct effect of complexity on training in IoMT

This section addresses hypothesis H2b which states, *"Complexity of IoMT positively influences training to use IoMT"*.

From table 6-1 it can be seen that complexity is having a direct and positive influence on training to use IoMT. AMOS reports (see table 6-1) show that a one standard deviation change in complexity affects a change of 0.349 standard deviations in training to use IoMT. The result can be interpreted in a way that as the complexity increases in using IoMT then usability of IoMT becomes that much more difficult leading to the necessity to increase the training. These results are confirmed by other researchers in the context of inventions and innovations in other fields, for instance, the research by Mairura (2016) who showed that in the context of automobile industries, with new inventions and innovations complexity and compatibility, issues may arise that may require re-training of workers. In another instance, it is important to recognize the complexities involved in the training itself. In such a situation, if users fail to see easiness in undergoing training due to reasons including the method of delivery of the training or the degree of difficulty or complexity associated with the training material then use or reuse of innovation or invention (Tristani et al., 2020). However, there are research outcomes that show that complexity is inversely related to training. Putteeraj et al. (2021) argue that increased complexity of the innovation or technological innovation can involve rigorous training and such training could act as an obstacle to the usage of a technology, which implies that the complexity of innovation should not lead to complex training. This indicates that regardless of the intricacies involved in technology, it is important to ensure training given is less complex, and to the extent needed. Thus, on the one hand, it is possible that technological innovations and inventions could be complex to use and on the other, there is a need to take training to learn how to use the innovations simpler. This indicates an inverse relationship between the complexity of an innovation that is diffusing and the need to undergo training to use the innovation. These arguments point toward the lack of a consensus amongst the researchers on what should be the relationship that should exist between the complexity of innovation and the training that needs to be undertaken by the user to use the technology. Thus, this research aligns with the findings of the researchers like Mairura (2016) who says that complexity is directly related to training.

In terms of the practical application of the concept, it can be seen from the results of this research that the higher the complexity of IoMT, the higher will be training requirements for the user to use and reuse IoMT. In addition, it is important to note that the higher the complexity of training, the lower will be the user's intention to use an innovation. These two complexities provide an indication to the manufacturers of IoMT to ensure that despite the complexities involved in making IoMT, such complexities should not hinder its usage. If usage is likely to be hindered due to complexities in technology, then the manufacturers must ensure proper training is provided to the users. Such training and training resources should be less complex for users to learn how to use IoMT leading to the use and reuse of IoMT, especially during the process of diffusion of IoMT. From the foregoing discussions, it can be seen hypothesis H2b stands supported and the explanation behind it.

6.3.4. The direct effect of compatibility on training in IoMT

This section addresses hypothesis H3b which states, *"Compatibility of IoMT positively influences training to use IoMT"*.

From table 6-1 it can be seen that compatibility directly and positively influences training to use IoMT. Further, it is important to note that one standard deviation incompatibility is likely to introduce a 1.4 standard deviation change in the training to use IoMT. While it seems to be an unrealistic statistic, it can be seen that a number of times an independent variable introduces a greater than one standard deviation change in the dependent variable when one standard deviation change takes place when using unstandardised regression. However, when standardised regression is used, it can be seen from table 6-4 that one standard deviation in compatibility introduces a 0.967 change in training to use IoMT, which is less than one. That compatibility is having a positive influence on training is confirmed by many researchers. For instance, Rogers (2003) argued that compatibility refers to the extent to which an innovation is congruent with an innovation. This implies that the higher the congruence, the higher will be the compatibility of innovation to the users and hence better acceptability of training in that innovation. Tristani et al. (2020) found out through their research on teachers' decisions to adopt teacher-training resources for inclusive physical education that training resources are essential. The researchers revealed that the design of resources and the presentation material of those resources influenced the teacher's decisions to adopt training resources, with a complex design of resources discouraging teachers from getting trained. Similar sentiments are echoed by others including Putteeraj et al. (2021) and Huang et al. (2020). While Putteeraj et al. (2021) argued that training needs are directly linked to compatibility in the context of assessing e-health adoption readiness using diffusion of innovation theory, Huang et al. (2020) measured compatibility using learning (a proxy for training (Fauth & González-Martínez, 2021) in the context of diffusion and adoption of an open-source learning platform. There is hardly any evidence of compatibility having any negative relationship with training or learning in the literature. This discussion clearly demonstrates that the result of this research aligns with already existing literature on the diffusion of innovation of the internet of medical things.

In practical terms, it can be seen that compatibility can be linked to some issues concerning training. For instance, compatibility is defined as the degree to which an innovation is perceived as being consistent with the existing values, needs, and past experiences of potential adopters (Roger, 1983). This was measured by one of the items in the research instrument, which stated that "using an IoMT is completely compatible with my current situation (CMP2)". This implies that healthcare professionals have a need for a technology like IoMT that is compatible with their profession. However, when one encounters the latest technologies or innovations or upgrades in IoMT (e.g., Heart rate monitors, (Ben Dhaou et al., 2021) then the continuous usage of IoMT may suffer due to possible compatibility problems. This could force the healthcare users to either abandon the existing devices and opt for the latest technologies or innovations or upgrades in IoMT or to learn more about those devices and make a decision to continue with the existing ones or adopt the latest technologies or innovations or upgrades in IoMT in conjunction with the new ones. In such a situation compatibility problem could arise concerning a number of factors. For example, interoperability problems, complexity problems, higher costs of switching over to the new technology or innovation or upgrade and the necessity to learn new technical skills are some of the problems that could stare at the healthcare professionals and push them into dilemma. One possible solution to overcome these problems could be appropriate training. The professionals could be training so that the

IoMT can be used with the least concerns. This will eventually lead to the usage of those new devices or upgrades or in combination with existing devices. Thus, it can be seen that the relationship between the compatibility of IoMT and training to use IoMT has been explained with the support of the literature and actual use in the healthcare industry. Although the literature is silent on how compatibility problems of IoMT influence training to use IoMT, there is some hint in the literature (Putteeraj et al., 2021), which shows that training could be positively driven during the diffusion of innovation by high compatibility of the innovation with the users' needs. Thus, it can be seen that the findings of this research add to the body of knowledge, which provides evidence of the existence of a clear positive relationship between the compatibility of innovation like IoMT and training to use that innovation. This finding is supported by two theories namely DoI and TPB. While DoI supports the diffusion of IoMT and the need for innovations like IoMT to be compatible with the needs of the users of that innovation, TPB explains the planned behaviour of the healthcare professionals in taking decisions to use or reuse a device based on training. The application of DoI and TPB in combination to understand the behaviour of healthcare professionals in their decision making when IoMT is still diffusing points towards early adopters and expands the application of those theories to explain the behaviour of healthcare professionals to use or reuse IoMT. This is a finding that is not found in the relevant literature. Late adopters might not face these compatibility problems as those would have been addressed by the challenges faced by early adopters already and solutions would have been found for those challenges. From the foregoing discussions, it can be seen hypothesis H3b stands supported and the explanation behind it.

6.3.5. The direct effect of motivation on continuous intention to use IoMT

This section addresses hypothesis H6 which states that *"Motivation to use IoMT positively influences continuous intention to use IoMT"*.

The results of this research show that motivation to use IoMT influences continuous intention to use IoMT directly and in a positive direction. AMOS report (see table 6-1) shows that a one standard deviation change in the positive direction in motivation as a construct exerts a 0.621 standard deviation change in continuous intention to use IoMT in the positive direction. Similar findings have been obtained by other researchers for instance Çolak and Kağnıcıoğlu (2021), Brauner et al. (2017) and Ramantoko et al. (2016) have investigated the relationship between motivation and behavioural intention in the acceptance of a technology or innovation. However, Yang and Koenigstorfer (2021) found a non-significant relationship between motivation and behavioural intention to use in their study on determinants of fitness app usage while Mtebe et al. (2016) found a negative relationship between motivation and behavioural intention to use multimedia-enhanced content in secondary schools. These contradictory outcomes pose a problem of lack of a consensus on the influence of motivation on behavioural intentions. However, the results of this research align with those of Çolak and Kağnıcıoğlu (2021), Brauner et al. (2017), and Ramantoko et al. (2016). Thus, it was found that the results of this research confirm the conceptualisation of motivation as influencing the use or reuse of continuous intention to use IoMT positively during the diffusion of IoMT. This indicates towards the early adopters because, when IoMT is diffusing, the motivation to use IoMT must first affect the early adopters as late adopters will derive motivation from the early adopters as a corollary.

From the practical side, it can be seen from the example of professionals being motivated to use IoMT because the facilities offered by the technology can enable the professional to improve the quality of healthcare services (Paul et al., 2021) that usage depends on the motivation of healthcare professionals. The example shows that the higher the motivation higher will be the use or continuous intention to use IoMT. For instance, shrinking sizes of sensors, lower power consuming devices, fast-changing information and communication technologies, increased wireless devices, better convenience and less interference with daily activities enable continuous monitoring of patients' health and makes healthcare decision making easy (Kyriakou et al., 2019; Wu et al., 2018; Yi et al., 2015). This motivates healthcare professionals to provide better services and improve the quality of service. Thus, the higher the motivation, the more continuous will be the monitoring of the health of patients and hence a need for continuous intention to use IoMT. This is supported by the self-determination theory, which says that types of motivation can be differentiated, and it is possible to see different types of motivation have operationally different catalysers, concomitants, and consequences (Deci et al., 2017).

To this effect, if SDT is applied and using the arguments of Gao and Bai (2014) it can be said that intrinsic motivation like perceived enjoyment of using IOT can encourage consumers to accept and use IOT. This implies that with regard to continuous intention to use IoMT the application of SDT can explain how the relationship between intrinsic motivation and continuous intention to use IoMT operates. That is to say, this research finds that the application of SDT can be expanded to explain and understand the influence of intrinsic motivation on continuous intention to use IoMT. This is a new finding as to date it appears no research has evaluated the operation of the relationship between intrinsic motivation and continuous intention to use IoMT applying SDT. From the foregoing discussions it can be seen that hypothesis H6 stands supported by our findings.

6.3.6. The direct effect of training on continuous intention to use IoMT

This section addresses hypothesis H7 which states that *"Training in IoMT positively influences continuous intention to use IoMT"*.

From table 6-1 it can be seen that training to use IoMT influences continuous intention to use IoMT directly and positively. It can be seen from table 6-1 that a one standard deviation change in the positive direction (increase) in training leads to a 0.152 standard deviation change in the positive direction (increase) in continuous intention to use IoMT in the positive direction. This result is similar to the results achieved by other researchers (Yousef et al., 2021; Schukat & Heise, 2021; Muqtadiroh et al., 2019) who agree that the higher the quantum of training or learning, the more likely the users will use and reuse or continue to use an innovation. However, Chen et al. (2021) caution that training is one of the facilitators of behavioural intention to adopt IoMT and can have a negative impact on the continuous intention to adopt IoMT if it is not satisfactory to users. Thus, it can be seen that literature has supported both positive and negative influences of training on continuous intention to use IoMT. Thus, during the diffusion of IoMT it can be seen that while training can facilitate continuous intention to use or reuse IoMT, at the same time if such training facilities are not satisfying the requirements of the healthcare professionals, then there could be a negative impact of training on continuous intention to use IoMT. Thus, this research confirms the findings of Yousef et al. (2021), Schukat and Heise (2021) and Muqtadiroh et al. (2019) who say that training to use innovation or technology positively influences the continuance of use by users. However, in the context of IoMT which is still considered an evolving technology the findings of this research show that early adopters act as a beacon to the late adopters of IoMT as any challenges faced by early adopters are addressed before the product reaches the late adopters. It is clear that training is an important factor that influences and hence if IoMT which comprises devices and equipment that use complex technologies, is to be accepted and continuously used then manufacturers should provide satisfactory training to the users including the healthcare professionals. The influence of training on behavioural intention to use or reuse or continue to use IoMT was explained by the theory of planned behaviour (TPB) and DoI. While TPB is used primarily to study human intentions and attitudes (Ajzen, 1985; Ajzen, 1991), DoI provides the basis for understanding at what stage (Rogers, 2003) of training, acceptance or use or reuse or continuance of IoMT takes place. According to TPB user's behaviour is influenced by their intention to behave whereas the intention is influenced by attitude, subjective norms, and perceptions of behavioural control (Septiani & Ridlwan, 2020). It is commonly utilised to anticipate intention and behaviour in the context of technology adoption in the medical field (Bronfman et al., 2021; Hennings & Herstatt, 2019; Ifinedo, 2018), and can therefore be used to assess IoMT acceptance behaviour of healthcare professionals based on training. Thus, the results of this research, which is the positive influence of training to use IoMT on continuous use of IoMT, are supported by the two theories, a finding not reported to date in the IoMT literature.

On the practical side of the use of the findings of this research, it can be said that the positive influence of training on continuous intention to use provides a basis for manipulating training as a construct to enable the healthcare professionals to use and continuously use IoMT. For instance, Rubí and Gondim (2019) argue that IoMT devices including ECG, blood pressure, blood oxygen saturation, pedometers, gyroscopes, GPS, relative air humidity and temperature measured using sensors when interconnected become complex to use. In such a situation training becomes essential. Training involves the training of healthcare professionals on using the IoMT devices and sensors to connect with the network, collect data, analyse data and make decisions. In addition, training should also address the easiness of learning through well-designed training material which will enable the healthcare professionals to undertake training. Furthermore, during diffusion training becomes not only important but also dynamic. This implies that if between the introduction of the IoMT and the final acceptance of IoMT, technology changes, then it is important training as a factor is also aligned with the changing technology and ensure that healthcare professionals are in synchronisation with the new technology. In addition, training also provides an opportunity to ensure that healthcare professionals learn the art of adding plug-ins to their existing IoMT thus upgrading the technology with minimum expenditure yet being in line with the changing technology. The importance of training is not well articulated in the extant literature and not many models are found in the literature with the exception of Al-Dhaen et al. (2021) that have employed training in IoMT as a factor. Thus, the findings of this research enrich the understanding of how to deal with difficult changes in technology during its diffusion by using training as a factor and continuing to use the existing IoMT devices with the current knowledge, acquiring new knowledge and gaining application knowledge through training. However, it is important to realise that if the training becomes difficult then there is a risk of the findings of this research being reversed, leading to a possible situation that shows that the higher the level of training, the lower will be the use or reuse of technology. . From the foregoing discussions, it can be seen hypothesis H7 stands supported and the explanation behind it.

6.3.7. Total effect of exogenous variables on Continuous Intention to IoMT use

Table 6-5 provides the total effect of the exogenous variables on endogenous variables. Table 6-2 provides the indirect effect of the exogenous variables on the dependent variable continuous intention to use IoMT.

Table 6-5: Total effect of exogenous variables on endogenous variables.

	Complexity_(CPX)	**Trialability_(TRI)**	**Compatibility_(CMP)**	**Observability_(OBS)**	**Relative_advantage_(RA)**	**Training_(TRN)**	**Motivation_(MOT)**	**Continuous_intention_(CI)**
Training_(TRN)	.349	.000	1.472	.000	-.343	.000	.000	.000
Motivation_(MOT)	.068	-.097	1.319	-.197	-.006	.000	.000	.000
Continuous_intention_(CI)	.095	-.060	1.043	-.122	-.056	.152	.621	.000

6.3.8. Total effect of relative advantage on continuous intention to use IoMT

From table 6-5, it can be seen that relative advantage indirectly but negatively affects continuous intention to use IoMT (-.056). That's to say that when relative advantage changes by one standard deviation in the positive direction, then continuous intention to use IoMT changes by 0.056 standard deviations in the negative direction. This is an anomalous situation. That is to say that if the relative advantage of IoMT is high, then logically it is not possible that continuous intention to use IoMT as where there is an advantage it is almost certain that users will continuously use IoMT and mediation by training will not be necessary. The explanation for this anomalous situation lies on the one hand in the negative relationship between relative advantage and training to use IoMT (regression weight -0.343) and the positive relationship that is found to exist between training to use IoMT and continuous intention to use IoMT, on the other. However, when relative advantage is low and hence the need for training is high then the continuous intention to use IoMT will be high. This situation is logical. However, this is only possible if there is a negative mediation between relative advantage and training. Thus, the results of this clearly demonstrate that the outcome of this research is valid for those situations where IoMT offers a lower relative advantage. Motivation has no role to play as relative advantage does not have any significant relationship with motivation. In real life how it could happen is explained as follows). Kwon et al. (2021) have identified the disadvantages of using certain IoMT devices. Table 6-6 shows that EEG suffers from the disadvantages like direct contact between the sensor and skin and signal quality depends on skin conditions. These disadvantages may require good expertise on the part of healthcare professionals to overcome the limitations posed by the sensors. Achieving such expertise may require a high level of training. This in turn will help the healthcare professionals to use and reuse the sensors by overcoming the disadvantage. These are new findings that add to the body of IoMT usage literature.

6.3.9. Total effect of complexity on continuous intention to use IoMT

From table 6-5, it can be seen that complexity indirectly affects continuous intention to use IoMT through the path CPX→TRN→CI. The total effect of complexity on continuous intention to use IoMT is positive (.095) (table 6-5). That is to say that when complexity is high yet continuous intention to use IoMT is high. This can be explained by the fact that training mediates between the complexity of IoMT and continuous intention to use IoMT in a way that complexity does not affect continuous intention to use IoMT inversely. The reason is that when complexity is high then the path CPX→TRN which has a direct and positive relationship ensures that high-level training is provided to the users which in turn ensures that the users use and continue to use the devices. However, the reverse does not happen that is when complexity is low in which case the training will be low and hence the continuous intention to use IoMT is low. The reason is that when the complexity of IoMT is low, then intend to use IoMT does not necessarily depend upon the mediator as users could use self-learning methods to use IoMT. The results thus are logical and acceptable. The mediation by training between the two latent variables complexity of IoMT and continuous intention to use IoMT is a new finding and adds to the body of knowledge concerning continuous intention to use IoMT.

6.3.10. Total effect of compatibility on continuous intention to use IoMT

From table 6-5, it can be seen that compatibility of IoMT influences continuous intention to use IoMT through two paths namely CMP→MOT→CI and CMP→TRN→CI. It can be seen that the total effect of compatibility on continuous intention to use IoMT is positive but indirect (1.043) (table 6-5). This implies that when compatibility changes by one standard deviation in the positive direction, then continuous intention to use IoMT also changes by one standard deviation approximately in the positive direction. Furthermore, the reverse can also be true. For instance, when compatibility decreases by one standard deviation, the continuous intention to use IoMT can also decrease by one standard deviation. Considering the fact that the paths CMP→MOT and CMP→TRN are both positive and direct and linking these two paths with MOT→CI and TRN→CI respectively which are also positively and directly linked, it can be seen that an increase in compatibility will directly and positively influence both motivation and training and hence continuous intention to use. This implies that both motivation and training mediate positively between compatibility and continuous intention to use IoMT which is a new finding. Similar results have not been reported in the literature concerning continuous intention to use IoMT.

As far as theoretical support for these results is concerned, it can be seen from chapter 3 that the theories of DoI, self-determination and TPB provide the basis for integrating the concepts of relative advantage, complexity, compatibility, motivation, training and continuous intention to use IoMT. An examination of the extant literature showed that no similar results have been reported in the literature except the one produced by Al-Dhaen et al. (2021) who reported the application of DoI theory only. Thus, this research expands the theoretical application of DoI in combination with self-determination and TPB, which together provides the support to explain the phenomenon of diffusion of IoMT embedded with AI, knowledge that is new.

It must be noted here that the constructs trialability and observability do not have a statistically significant relationship with motivation and hence have not been discussed. The reason for the lack of a statistically significant relationship between the two constructs and motivation has been discussed (in section 5.14.3).

6.4. Importance of associations between the exogenous variables

From table 6-6 it can be seen that the associations between the exogenous variable's relative advantage, compatibility, trialability and observability are statistically significant while the ones involving complexity are not found to be statistically significantly valid.

Table 6-6: Statistically significant covariance between exogenous variables.

			Estimate	**S.E.**	**C.R.**	**P**	**Label**	**Similar results found in the literature**
Observability_(OBS)	<-->	Trialability_(TRI)	.561	.074	7.559	***	par_13	Hubert et al. (2019); Al-Rahmi et al. (2019); Shiau et al. (2018)
Compatibility_(CMP)	<-->	Trialability_(TRI)	.481	.064	7.508	***	par_15	Hubert et al. (2019)
Compatibility_(CMP)	<-->	Complexity_(CPX)	-.031	.035	-.883	.377	par_16	Venkatesh & Davis (1996)
Trialability_(TRI)	<-->	Complexity_(CPX)	.078	.051	1.534	.125	par_20	Venkatesh & Davis (1996)
Observability_(OBS)	<-->	Compatibility_(CMP)	.311	.050	6.238	***	par_21	Al-Rahmi et al. (2019); Shiau et al. (2018)
Relative_advantage_(RA)	<-->	Compatibility_(CMP)	.512	.060	8.509	***	par_22	Al-Rahmi et al. (2019); Shiau et al. (2018)
Relative_advantage_(RA)	<-->	Trialability_(TRI)	.412	.067	6.176	***	par_23	Al-Rahmi et al. (2019); Shiau et al. (2018)
Observability_(OBS)	<-->	Complexity_(CPX)	.083	.045	1.858	.063	par_25	Venkatesh & Davis (1996)
Relative_advantage_(RA)	<-->	Observability_(OBS)	.256	.053	4.808	***	par_29	Al-Rahmi et al. (2019); Shiau et al. (2018)
Relative_advantage_(RA)	<-->	Complexity_(CPX)	-.031	.042	-.744	.457	par_32	Venkatesh & Davis (1996)

This implies that complexity as an exogenous variable does not influence the relationship between other exogenous variables and the endogenous variables. That there is no correlation between complexity and other exogenous variables were not found in the extant literature, except rare research outcomes like the one produced by Shiau et al. (2018). This is a new finding. This implies that complexities found in IoMT do not affect the other diffusion factors namely relative advantage, compatibility, trialability and observability. That is to say that complexity individually affects training and hence continuous intention to use. However, the lack of any statistically significant association between the exogenous variables' relative advantage, compatibility, trialability and observability on the one hand and complexity on the other was unexpected and contrary to the findings in the literature. For instance, Al-Rahmi et al., (2019) found a correlation among all the five exogenous variables which are contrary to the findings of this research. In practical terms, the lack of statistically significant association between complexity and the remaining four constructs shows that the complexity of IoMT is independent of the four factors of diffusion that affect the adoption of IoMT. That is to say, that complexity will not change when any one of the four-factor changes. Although this conclusion may raise concerns if it has to be accepted, in real life this kind of situation could be witnessed. For instance, in regard to heart rate monitors the complexity of the technology built within the IoMT devise could be less concerning to users and may not impact the advantage the device could offer in terms of providing better healthcare to the patient or compatibility for usage. In addition, trialability and observability are unlikely to be affected by the complexity as long as the device supplier enables some sort of demonstration of the product. It is therefore possible to infer that the findings of this research show that complexity as a construct affecting diffusion of IoMT can be dealt with in isolation while determining the continuous intention of healthcare professionals to adopt it.

However, the relationship between relative advantage and compatibility on the one hand and training on the other can be influenced by the association that exists amongst the four factors namely relative advantage, compatibility, trialability and observability. That is to say that the association between compatibility and relative advantage can affect the relationships between RA→TRN→CI, CMP→MOT→CI and CMP→TRN→CI. That is to say when relative advantage or compatibility increases, then compatibility or relative advantage will increase and vice versa. These arguments can be extended to trialability and observability. Overall, it can be said the total effect of the two exogenous variables' relative advantage and compatibility on continuous intention to adopt IoMT is affected by the association that exists amongst the four exogenous variables relative advantage, compatibility, trialability and observability. This is a new finding. Similar arguments were not found in the extant literature.

An explanation of this in practical terms can be that a wearable like a heart rate monitor could be continuously used by the healthcare professionals because the association between relative advantage, compatibility, trialability and observability is expected to motivate healthcare professionals to use and reuse the IoMT. In the process, if those professionals face challenges like a demonstration of how the heart rate monitor works and how to use those monitors then trialability and observability will be useful and could be associated with the relative advantage the wearable could provide and the compatibility it can offer.

Further to discussing the entire results of the exogenous variables on endogenous variables, the next section discusses the impact of moderators on the valid relationships.

6.5. Importance of Moderators

The results of this research consideration of three moderators in this research namely, artificial intelligence awareness, novelty-seeking behaviour and age. The results are tabulated in table 6-7.

Table 6-7: Moderation by Artificial intelligence awareness (AWS), Novelty seeking behaviour (NS) and Age.

Moderated relationships	Moderator	Result	Authors who have achieved similar results
Moderation of (RA-TRN) relationship by AWS	Artificial intelligence awareness (AWS)	Supported	Khakurel et al. (2018); Guerra (2018)
Moderation of (CPX-TRN) relationship by AWS	Artificial intelligence awareness (AWS)	Supported	Khakurel et al. (2018); Guerra (2018)
Moderation of (CMP-TRN) relationship by AWS	Artificial intelligence awareness (AWS)	Rejected	Ream et al. (2018); Almansoori et al., 2021
Moderation of (MOT-CI) relationship by NS	Novelty seeking behaviour (NS)	Rejected	Schukat and Heise (2021); Dionika et al., (2019)
Moderation of (TRN-CI) relationship by NS	Novelty seeking behaviour (NS)	Rejected	Schukat and Heise (2021); Dionika et al., (2019)
Moderation of (MOT-CI) relationship by Age1	Age	Rejected	Nikolopoulou et al., (2021); Kousloglou et al., (2021)
Moderation of (TRN-CI) relationship by Age1	Age	Rejected	Kousloglou et al., (2021); Nikolopoulou et al., (2021)

The results tabulated in table 6-7 and explained (in section 5.14.4) show that artificial intelligence awareness as a moderator does not moderate the statistically significant relationship between

The results of moderation (table 6-7) show that only two relationships namely relative advantage – training (RA-TRN) and complexity – training (CPX-TRN) are moderated by artificial intelligence awareness (AWS). Thus, the inferences that could be drawn are that artificial intelligence awareness does not affect the relationships between compatibility and training in IoMT. Compatibility indicates the ability of the device to satisfy the needs of users. When compatibility needs to be enhanced then training needs to be enhanced too, to ensure continuous intention to use. Such requirement of enhancing the compatibility of an IoMT device happens when technology changes or upgrades are announced by the makers of the device, or an innovation occurs on the horizon and users are forced to adopt those enhancements. In such a situation, technologies like artificial intelligence are unlikely to moderate the relationship at all as the independent variable compatibility is seen to wield a large influence on the dependent variable training as explained by the regression coefficient of 1.472 reported by AMOS (see table 6-1). These interpretations explain the lack of statistical significance of the moderation of the relationship by artificial intelligence awareness.

Finally, the lack of statistical significance of the moderation of the relationships MOT-CI and TRN-CI by age and novelty-seeking has been explained, i.e., in section 5.14.4 of chapter 5. Thus, based on the foregoing discussion, it is now possible to answer the research questions.

RQ1: What factors determine the continuous intention of healthcare professionals to use AI-based IoMT that is still diffusing?

From the results of this research provided in table 6-2, and after discussion in section 5.14.3, it can be seen that only three of the five DoI factors (namely relative advantage, complexity and compatibility) are found to have an indirect, but statistically significant, effect on continuous intention to use AI-based IoMT. That is to say that during the diffusion of AI-based IoMT, the relationship between RA, CPX and CMP on the one hand, and continuous intention to use IoMT on the other, is found to be operational; and can be manipulated to enhance the continuous intention of the healthcare professionals to use

IoMT. Explanations on how the results can be compared with the current literature are provided in section 6.3 of this chapter. Thus, it can be concluded that RQ1 has been answered.

RQ2: Do mediators and moderators affect the relationship between determinants of the continuous intention of healthcare professionals to use AI-based IoMT and continuous intention of healthcare professionals to use AI-based IoMT during diffusion of AI base IoMT?

Chapter 3 provides the research model in which motivation and training to use AI-based IoMT are shown to mediate between the five DoI factors and CI to use AI-based IoMT. Results of the data analysis show that motivation to use AI-based IoMT mediates between compatibility to use AI-based IoMT and CI. Similarly, training was found to mediate between the relative advantage of AI-based IoMT, the complexity to use AI-based IoMT and the compatibility to use AI-based IoMT and CI. It was found that trialability and observability do not influence continuous intention to use IoMT at all. The results obtained in this research have been explained in section 6.5. Three different moderators were studied as affecting the continuous intention to use IoMT during diffusion. It was found that only AI awareness moderates between two factors of DoI and training to use IoMT, while neither novelty-seeking behaviour nor age was found to be statistically significant in moderating the relationships between motivation and training to use IoMT. These results have been explained in section 5.14.4 of chapter 5. Thus, it can be concluded that RQ2 has been answered.

RQ3: Which of those mediators and moderators enable the determinants to influence the continuous intention of healthcare professionals to use AI-based IoMT during diffusion of AI base IoMT?

From section 6.5 in this chapter, it can be seen that motivation to use IoMT mediates between compatibility to use AI-based IoMT while training to use AI base IoMT was found to mediate between relative advantage, complexity and compatibility of AI-based IoMT on the one hand and continuous intention to use AI-based IoMT on the other. Amongst these relationships, it is compatibility that was found to be the dominant determinant of the continuous intention of the healthcare professionals to use AI-based IoMT. Compatibility acts as the determinant of CI through the mediation of both motivation and training to use IoMT while relative advantage and complexity act as determinants of continuous intention to use IoMT. These results imply that training and motivation could encourage healthcare professionals to continuously use IoMT when relative advantage, complexity and compatibility have a lower influence on CI when IoMT is still diffusing. This is practically explained under sections 6.3.1 – 6.3.9. The explanations under section 6.3 clearly show that these findings are unique and similar findings do appear to have been reported in the relevant literature.

As far as moderators are concerned it is AI awareness that is found to be a sole moderator of two relationships. The meaning of this moderation has been explained in section 5.14.4, in chapter 5, and a comparison with the literature has been provided. Overall, it can be said that where IoMT devices have AI technology embedded in them, AI awareness is required to be used to enhance the operation of the relationships relative advantage-training and complexity-training. Thus, it can be concluded that RQ3 has been answered.

6.6. Chapter summary

The discussion in this chapter has provided the findings that have emerged from this research. The chapter has dealt with various relationships and their meaningfulness in explaining the influence of the exogenous on the endogenous variables. The discussions show that the results produced in this research have either not been reported by other researchers or in line with the research outcomes produced by some of the researchers or contradict some other researchers based on theory and practice. For instance, the lack of support for the influence of exogenous factors' relative advantage and complexity on motivation is not supported by the extant literature, which, is to the best of our knowledge, a new finding. However, the lack of support for trialability and observability is in line with the literature. Additionally, the support for the influence of compatibility on motivation is in line with extant literature. Thus, this research has provided an understanding of the key factors that aid in the diffusion of the AI-based IoMT with the intervention of motivation as a behavioural construct. However, concerning training as the behavioural construct all the three diffusion factors namely relative advantage, complexity and compatibility were found to influence it. Here there are contradictory findings. For instance, the negative influence of relative advantage on training to use IoMT is a new finding not supported by extant literature. This implies that when the relative advantage of IoMT is low then the training required may be high. Although there is a paucity of literature on the relationship between relative advantage and training, the finding that there is a negative relationship between the two is new knowledge. As far as other relationships are concerned namely complexity → training and compatibility → training the findings of this research are in line with the extant literature. An important feature of this research is the association between the exogenous variables that exert indirect pressure on the exogenous variables. This is a new finding not reported by any publication in the extant literature. Here four variables of DoI namely relative advantage, compatibility, trialability and observability are found to come into play while complexity was found to act independently. There was no association found between complexity and the remaining four exogenous variables. This is another new finding not reported in any study in the extant literature. Association between the exogenous variables provides insights into how those variables can be controlled to achieve integration with behavioural variables.

With regard to mediators, these research findings provided new knowledge on the integration of behavioural variables motivation and training with the diffusion of innovation factors and their mediation in the path between DoI factors and continuous intention to use IoMT. This in turn provided knowledge on how to enhance the diffusion of IoMT and continuous intention to use IoMT using behavioural attributes. There is hardly any research outcome found in the extant literature on this aspect although there is support for individual relationships namely motivation and continuous intention and training and continuous intention in the extant literature. The relationship between the diffusion factors, motivation and training has been discussed already earlier.

Another important aspect was the ability of the model to determine the total effect of all the exogenous variables on endogenous variables. This is new knowledge. There are no specific research outcomes that have been reported in the extant literature on this effect.

Finally, the results of moderators reported in this research find contradictory support in the extant literature. While the lack of support for the moderation of the relationships between motivation, training and continuous intention to use IoMT by novelty-seeking behaviour and age is contradictory but finds support in the extant literature. The same can be said of the moderation of the relationship between relative advantage-training, complexity-training and compatibility-training by artificial intelligence-based IoMT. Thus, this chapter provides the basis to conclude the research which is provided in the last chapter.

7. Chapter 7: Conclusions

This chapter concludes the research. The various aspects of this research including the achievement of the aim and objectives of the research, answering the research questions, contribution to knowledge, theory, methodology and practice, limitations of this research and the recommendations for future research are discussed in this chapter.

7.1. Assessing the achievement of the aim and objectives

This research aims to examine the determination of the continuous intention to use IoMT of healthcare professionals when IoMT embedded with another technology namely artificial intelligence is still diffusing. The research aim was achieved and explained in the following discussion.

The problem statement in chapter 1 points out that there is a need to understand the use and reuse of IoMT, which is the continuous intention of healthcare professionals to use IoMT when IoMT is still diffusing. The twin phenomena of incomplete diffusion of IoMT and the rapid changes that occur in quick succession in IoMT technology preventing a previously adopted technology can create challenges to those professionals in decision-making. These challenges also lead to fresh challenges like determining the acceptance, usage and continuous intention to use IoMT in the context of healthcare professionals. In addition, there are other problems like the concurrent diffusion of technology. These challenges have posed problems to healthcare professionals and healthcare providers in terms of offering the latest and the best healthcare to patients. Thus, the aim of this research was set based on the problem statement which was to examine the determination of the continuous intention to use IoMT of healthcare professionals when IoMT embedded with another technology namely artificial intelligence is still diffusing. This aim was achieved by examining the relationship between the factors that support the diffusion of innovation (the independent variables) that is relative advantage, complexity, compatibility, trialability and observability of IoMT and the continuous intention to use IoMT (the dependent variable). This relationship was tested in the presence of interventions namely motivation and training of healthcare professionals to continuously use IoMT on the one hand and artificial intelligence awareness, novelty-seeking behaviour and age of healthcare professionals on the other. A theoretical model was drawn (see figure 3.7) to firstly examine the various relationships based on theories including diffusion of innovation, self-determination theory, theory of planned behaviour and unified theory of acceptance, and use theory (UTAUT); and secondly to undertake a critical review of the literature (see chapter 2). Chapter 3 describes how the theoretical model with the various assumed relationships was developed to examine the relationship between the independent and dependent variables using hypotheses as the starting point. Amongst the interventions, motivation and training to use IoMT were brought in as mediators between the independent and dependent variables which was supported by both theory and literature review. The relationship between independent variables and motivation as a mediator was tested using Self Determination Theory (SDT) while that of training to use IoMT was tested using the Theory of Planned Behaviour (TPB) (Chapter 3). In addition, while examining the relationship between the independent and dependent variables in the presence of mediators, the literature review showed that certain factors like artificial intelligence awareness, age and novelty-seeking behaviour can act as moderators. Such moderators were included to gain a more comprehensive picture of the relationship between the independent and dependent variables aided by specific theories namely DOI and UTAUT. Thus, using relevant theories, and the outcome of the critical review of the literature related to different investigations conducted in the area of the central issue of continuous intention to use IoMT allowed us to undertake an examination of the independent and dependent variables in the domain. The developed hypotheses were then tested. In short, the examination revealed that one independent variable namely compatibility was the only statistically significant variable that influenced the dependent variable through both motivation and training to use IoMT. Relative advantage and complexity use of IoMT were found to influence the independent variable only through training to use IoMT. Amongst the moderators, only artificial intelligence awareness was found to moderate the relationships (relative advantage-training) and (complexity-training). No other moderators were found to moderate any other relationship.

The entire examination was conducted when IoMT embedded with artificial intelligence was still diffusing. This was confirmed by the responses given by the respondents with regard to the five constructs that aided the diffusion of IoMT and the continuous intention to use IoMT (see section 5.2.2). In addition, wearables are undergoing continuous upgrades. For instance, Koralli and Mouzakis (2021) argue that wearables undergo upgrades and cite the example of the use of new technologies that could replace batteries required to power those wearables. Koralli and Mouzakis (2021) explain that one-time-use or rechargeable batteries used in wearables could be replaced by devices that could retrieve thermoelectric energy from the human body heat via the Seebeck effect (Liu et al., 2021). These changes or upgrades can also affect the relationship between diffusion factors and continuous intention to use IoMT. These upgrades could be novel discoveries and could potentially affect the continuous intention to use IoMT. So, novelty was found to be an important aspect affecting the continuous use of an IoMT during its diffusion. The responses related to the construct of novelty-seeking show that healthcare professionals are keen to use those devices that are novel. In addition, responses to the construct continuous intention to use IoMT also show that IoMT will be continuous i.e., responses to item “I will continue using IoMT applications in the future” fall in between the responses neutral (3) and agree (4) used in future by the respondents. These arguments imply that if there is a novel wearable device, then healthcare professionals could consider discarding the usage of the current device in favour of the new one. However, the results of the examination showed that novelty-seeking behaviour was not a significant intervention as a moderator. Thus, if the results of the responses for the construct novelty-seeking behaviour are taken in isolation then it is possible to conclude that incomplete diffusion of IoMT can happen if there is a novel device that intersects the current usage of IoMT devices. However, if novelty-seeking behaviour is viewed as a moderator, then based on the results of this research it is reasonable to argue that upgradations are unlikely to affect the continuous intention to use IoMT in future by the respondents.

Another important piece of evidence that was obtained during the examination of the model was the concurrent diffusion of both IoMT as innovation and artificial intelligence as new technology. The examination revealed that while DoI as a theory provided the basis to conclude the influence of the DoI factors on the dependent variable, at the same time no research outcome has examined the usefulness of DoI to understand the concurrent diffusion of two technologies at the same time. The nearest example to this phenomenon was the research by Lin (2021) who studied the recurrent diffusion of innovation using the theory of DoI but not concurrent diffusion. This is the first-time research that has investigated the concurrent diffusion of two new technologies and demonstrated that one technology (IoMT) acts as the determinant of continuous intention to use during diffusion, while the other technology (artificial intelligence awareness) can act as a moderator for certain relationships namely DoI factors and continuous intention to use IoMT during diffusion. This is a new finding. Based on the above it can be concluded that the aim of this research has been achieved.

Five objectives were set for this research to achieve the aim. The first one was to examine the current literature on factors influencing continuous intention to use IoMT with built-in artificial intelligence during its diffusion as the extent to which these factors could determine continuous intention to use IoMT during its diffusion is not well understood in the current literature. The literature review provided some evidence that showed that the primary factors that could influence continuous intention to use IoMT were the five factors identified by the theory of diffusion of innovation namely relative advantage, complexity, compatibility, trialability and observability of IoMT (Rogers, 2003). The evidence available in the literature was inconclusive, not generalisable and did address the diffusion aspects of IoMT and its continuous usage by healthcare professionals. Use, reuse and recurrent use of IoMT and its predictability are not well addressed in the literature with the number of publications available in the literature being far and few (Lin et al., 2021). Further, diffusion can be complete, partial or incomplete (Ouédraogo et al., 2019; Sahin, 2006). This adds to the complexity of the problem in determining the continuous intention to use IoMT. Literature shows that investigations have been called for by researchers to investigate the extent of diffusion of IoMT or IoT in the healthcare sector. Tables 2.6 – 2.10 provide the example of researchers who have suggested that the relative advantage, complexity, compatibility, trialability and observability of a diffusing IoMT can form the basis to investigate the continuous intention to use IoMT (section 2.14.1). These five factors have been depicted as determinants of continuous intention to use IoMT in this literature based on the support of some of the papers that were considered important for this research (e.g., Chen, 2019; Baudier et al., 2019; Ahmad et al., 2020; Venkatesh et al., 2012; Lee et al., 2011). However, section 2.14 also shows that researchers (Hwang et al., 2021; Liao et al., 2021; Szejda et al., 2020) have recommended the need to consider interventions in the path linking the five factors identified by the theory of DoI and continuous intention to use innovations. Thus motivation, training, artificial intelligence awareness, novelty-seeking behaviour and age were identified as interventions based on prior research (see section 2.14). Justifications for the choice of the factors that influence continuous intention to use IoMT are provided in the theoretical framework in Chapter 3. Thus, it can be concluded that the first objective has been achieved.

The second objective was the determination the relationship between the various factors identified as affecting continuous intention to use IoMT and continuous intention to use IoMT and develop appropriate hypotheses. This was achieved in chapter 3 in which a complete discussion has been provided on how the relationships between the various factors identified as affecting continuous intention to use IoMT and continuous intention to use IoMT have been translated into a theoretical model (see figure 3.7). The chapter shows that five constructs that aid in the diffusions of an innovation which is IoMT namely the relative advantage, complexity, compatibility, trialability and observability were identified as the determinants of the continuous intention to use IoMT. However, motivation and training were identified as interventions in the path relating the determinants to continuous intention to use IoMT. The theory of DoI, Self Determination Theory and Theory of Planned Behaviour were used to explain the relationship. Furthermore, the moderators were added to the theoretical model to explain how the relationships between the exogenous and endogenous variables could be better explained and tested. Artificial intelligence awareness, novelty-seeking behaviour of users of IoMT and the age of those users were involved in the research as interventions which provided support to enhance the explanatory power of the model and to understand how continuous intention to use IoMT could be determined. DoI provided the support to include artificial intelligence awareness as a moderator while UTAUT provided the basis to include novelty-seeking behaviour and age as moderators. Hypotheses have been developed based on research questions to be answered and the theoretical support outlined in every section that concern the hypothetical relationships identified in this research in chapter 3. Hypotheses were linked to the research questions. These arguments lead to the conclusion that the second objective has been achieved.

The third objective of developing and drawing the methodological framework for the research has been discussed in chapter 4. This methodology enabled the researcher to test the theoretical model and the hypotheses developed and drawn to test whether the various relationships depicted in figure 3.7 are supported are rejected. Testing the hypotheses led the researcher to answer the research questions which have been discussed in chapter 6. The chapter shows that positivist epistemology and objective ontological stance have been adopted as part of the research philosophy chosen for use in this research. In addition, the chapter provides a clear idea of the choice of the research approach and method used for this research which is the deductive approach and quantitative research method. It can be seen from sections 4.2 to 4.4 that the choice of the research philosophy, approach and method has been justified with the support of relevant methodology literature and various other researchers. The chapter discusses the research design and strategy which provide an idea about the various steps involved in data collection and analysis. This chapter provided the basis for chapter 5, which discusses the data analysis aspects. Thus, it can be concluded that the third objective has been achieved.

The fourth objective concerns evaluating the various relationships through statistical analysis and testing the hypotheses using the findings derived from the analysis. A thorough and rigorous data analysis was carried out using many statistical principles to assess the reliability and validity of the data collection instrument, collected data and the model. Structural equation modelling was used to conduct confirmatory factor analysis and path analysis. This enabled the researcher to find out the optimum number of items that need to be used to test the model and the various relationship between the exogenous and endogenous variables. The results of the analysis provided knowledge on which relationships amongst the latent variables are statistically valid and which hypotheses are valid. A separate section that explained the effect of the moderators on the various relationships between exogenous and endogenous variables enabled the researcher to discover which moderators affected the relationships. They modelled to conclude which hypotheses were supported and which were not. It was seen that diffusion was not affected by all five exogenous variables. Trialability and observability were not found to affect the diffusion. The paths between the remaining three exogenous variables and the determined endogenous variable showed that the path involving the mediator motivation is only affected by compatibility, whereas the path involving the mediator training is affected by relative advantage, complexity and compatibility. As far as the moderator is concerned, only artificial intelligence was found to affect the paths (relative advantage - training) and (complexity – training). The rest of the moderators were not found to be statistically significant. The findings derived in this chapter enabled the researcher to find the hypotheses that were supported and rejected in table 5-42.

This chapter thus provided the basis for the evaluation of those findings in the next chapter, and it can be concluded that the fourth objective has been achieved.

The fifth objective pertains to the evaluation of the findings with relevant literature and the evaluation was used to check whether the research questions have been answered or not. This aspect has been completely discussed in chapter 6 and the three research questions have been answered which enabled the researcher to conclude that the fifth objective has been achieved.

The sixth objective related to the conclusions of the research in terms of the contributions to knowledge, theory, methodology and practice and filing the identified gaps in the literature and recommending future areas of research based on the limitations of this research are discussed next.

7.2. Contribution to knowledge

This research contributes to the body of knowledge concerning the intention of healthcare professionals to continuously use IoMT embedded with artificial intelligence when it is still diffusing. The following discussions provide an idea about the contributions this research makes to knowledge.

7.2.1. Contribution 1: Bridging the gap concerning continuous intention to use IoMT

Foremost the outcome of this research fills the gap in the literature related to the determination of the continuous intention of the healthcare professionals to use IoMT.

According to Tsourela and Nerantzaki (2020) (see also Lee & Lee, 2020) literature is silent on how to determine the usage of IoT systems and ensure continuous usage of IoT systems from different perspectives. Further, in a situation where IoMT is continuously changing and has embedded in complex technologies like AI the perspective of the healthcare professionals with regard to continuous usage of IoMT is expected to change frequently. While some researchers (Wolken et al., 2018; Malik et al., 2017) have argued that there is a need to understand IoMT as an evolving and diffusing technology and hence needs to be investigated how it is being accepted and used or reused by users, at the same time some others have simply argued that there is a need to examine IoMT from the technical aspects (Gatouillat et al., 2018; Taylor et al., 2018). This research has combined both and investigated the concept of continuous intention to use IoMT and its determination and brought out significant discoveries.

IoMT is a new concept derived from IoT and is an innovation. Examples include Fitbit Aria, iHealth Sense, Withings Pulse O2, iHealth Track, Mi Electric Toothbrush, iHealth View, Garmin Vivofit, Mi Body Composition Scale, Fitbit Alta HR, Withings Steel HR, iHealth Core, Garmin Forerunner 630 and Misfit Vapor (Mavrogiorgou et al. 2019). All these devices are being upgraded now and then and new models are being brought out in rapid succession. For instance, Rainmaker (2021) has argued that Fitbit Alta HR Charge 5 is an upgrade of Charge 4 and has newer features. Fitbit Alta HR Charge 5 is wearable and has one of its functions as a high and low heart rate notifier. This has serious implications with regard to the users as well as suppliers because even before users can fully utilise and get benefitted from Charge 4, a new model Charge 5 arrives in the market and users land into a dilemma on whether to discard the current device being used and adopt a new one or continue to use the existing one. Their dilemma becomes a concern, even more, when the cost of the new devices is found to be prohibitively high and implementing the device raises serious challenges. Challenges like new training to be given to users the need for changes in interfaces with other equipment and the change in the way data is collected and analysed are common (see section 5.14.3). In addition to these challenges, the new devices bring in requirements that may need existing facilities to be changed to accommodate the new device which is another serious problem as this may cause additional expenditure. These aspects need to be understood and determined before an appropriate decision is taken by the users to either continuously use the current devices or to go in for new devices. The current knowledge about IoMT and its continuous use does not address these aspects (Salleh & Daud, 2019; Padyab et al., 2019; Jiang et al., 2019; Jalali et al., 2017). The reason why this has attracted attention is the fact that lack of knowledge about the continuous intention to use IoMT can have serious repercussions on the healthcare support provided to the patients as also depriving the patients of the best medical care possible if a new device is not used by replacing the current device, thus questioning the continuous intention to use IoMT. The viability of continuous intention to use or implement a new invention or innovation also comes into question. These are major contradictions. Any method to overcome the contradiction and determine the continuous intention to use IoMT thus gains currency. This research has identified ways to overcome these contradictions to some extent.

7.2.2. Contribution 2: Towards an understanding the diffusion of IoMT

Literature shows that another important challenge that innovators face during the process of the diffusion of technological innovation is the user behaviour which is not easy to understand as technologies do not automatically lead to behavioural intention to use IoMT (Lee & Shin, 2018). This is applicable to any technology which includes IoMT embedded with artificial intelligence. This is another area that was addressed in this research. Finally, there was another important phenomenon that required attention which is that two new technologies were diffusing at the same time. Until now there is no evidence of any research outcome found in the literature concerning the diffusion of an innovation which shows that the theory of DoI has been applied to explain the concurrent diffusion of two new technologies as the original theory was developed only to address the diffusion of one single innovation (Lin, 2021). The one exception that comes nearer to this argument is the investigation carried out by Lin (2021) who studied the recurrent diffusion of one single innovation using the theory of DoI and not concurrent diffusion. This study has investigated this aspect also.

As mentioned in section 2.14.1 in order to determine the continuous intention to use IoMT by healthcare professionals during its diffusion, this research used the theory of diffusion of innovation an argument supported by the extant literature (Emani et al. 2018; Lee et al. 2011). Dooley (1999) and Stuart (2000) observe that in research concerning several areas including public health, technology and education, Rogers' theory has been widely used to address technology diffusion and adoption. Rogers (2003) who is the original proponent of the theory of DoI, identified five factors namely relative advantage, complexity, compatibility, trialability and observability as affecting diffusion. It was further posited by Rogers (2003) that diffusion factors could be used to determine the rate of adoption of an innovation that is IoMT. Thus, the five factors were identified as the basic constructs that could be used to explain the diffusion of IoMT and its usage. Based on the current evidence available in the literature the factors were conceived as determinants of the rate of adoption of an innovation (Putteeraj et al., 2021; Daragmeh et al., 2021; Shiau et al., 2018; Burgess et al.,2017; Zhang et al., 2015). However, the main concern of this research was to determine the use or reuse or recurrent use or continuous intention to use IoMT and not the rate of adoption, which is not addressed in the literature (Lin, 2021). This is about the gap concerning the gap in literature concerning the importance of those diffusion constructs that were investigated to determine the continuous intention to use IoMT. Literature shows that diffusion does not automatically end in the usage of innovation as many innovations are found to be discontinued during the process of diffusion due to uncertainties (Sahin, 2006). At the same time, it could be the theory of innovation that can help overcome the uncertainties, for instance, compatibility can be an important factor to overcome uncertainties (Ionas, 2014; Lee, 2004). Thus, this research investigated the influence of the five exogenous factors namely relative advantage, complexity, compatibility, trialability and observability concerning the diffusion of IoMT with built-in artificial intelligence on the continuous intention to use IoMT of the healthcare professionals taking into account the behavioural attributes motivation and training to use IoMT as mediators and artificial intelligence, novelty-seeking behaviour and age as moderators. A theoretical model was drawn to determine the continuous intention to use IoMT during its diffusion, using the five exogenous constructs identified by the theory of DoI, mediators and moderators (see figure 3.7), which was tested and shown that it is possible to determine the continuous intention to use IoMT with built-in artificial intelligence. The results obtained and reported in chapter 5 and the discussions on those findings provided in chapter 6 clearly show that relative advantage, complexity and compatibility can indirectly influence the continuous intention to use IoMT with built-in artificial intelligence and determine the use, reuse or continuous use of the continuous intention to use IoMT with built-in artificial intelligence. This is new knowledge as there is no similar research outcome that has shown that three of the five DoI constructs can determine a new phenomenon of use or reuse or continuous use of the continuous intention to use IoMT with built-in artificial intelligence.

7.2.3. Contribution 3: Determination of the continuous intention to use IoMT during concurrent diffusion of two innovations

This is concerning the utility of the exogenous and endogenous constructs in determining the continuous intention to use IoMT during the concurrent diffusion of two innovations. While the research outcomes of Lin (2021) found that recurrent use of innovation can be determined using DoI constructs, it did not address the concurrent diffusion of two technologies. This research has been able to determine the continuous intention to use IoMT with built-in artificial intelligence when both IoMT and artificial intelligence are diffusing at the same time. In section 7.2. It has been shown that DoI constructs defined the diffusion of IoMT as a determinant and artificial intelligence awareness was used as the moderator of the diffusing IoMT. This conception is new knowledge as such a conception enabled the researcher to use the five DoI constructs to understand the way both IoMT and artificial intelligence affect the continuous intention to use IoMT with built-in artificial intelligence concurrently. To the knowledge of the researcher, a similar conception has not been attempted in any other innovation research, particularly in the areas of IoMT and IoT with the sole exception of Aldhaen et al., (2021). This publication was produced by Aldhaen et al., (2021) and is based on this research.

The next aspect in the research was the importance of behavioural aspects of the healthcare professionals that have bearing on the diffusion of an innovation, which has been shown by Lee and Shin (2018) to affect the continuous intention to use an innovation. While literature shows that a number of such user behaviour based concepts including workload and stress (Malik et al., 2021; Baskaran et al., 2020; Agboola & Olasanmi, 2016), language barrier (Richardson, 2011), culture (Krey, 2020; Wickramasinghe, 2018; Alshare et al., 2011), social environment (Yang Meier et al., 2020;

Wickramasinghe, 2018), Trust (Arfi et al., 2021; AlHogail, 2018; AlHogail, & AlShahrani, 2018, usage of IoMT, motivation to use IoMT (Tűrkeș, et al.,2020; Baudier et al., 2019; Ahn et al., 2016) training to use IoMT (Hassanien et al., 2020; Rajmohan & Johar, 2020; Li et al., 2018; Thibaud et al., 2018; Shashank & Consultant, 2017) can affect the diffusion of innovation and its eventual use. This research chose only the motivation and training of healthcare professionals to use IoMT as representing user behaviour constructs. Taking the support of the conceptualisation developed by Al-rahimi et al. (2019), in this research the above two concepts were introduced in the path between the exogenous variables and continuous intention to adopt IoMT as mediators which were supported by the literature and the Self Determination Theory and TPB (see section 3.3.3). The introduction of user behaviour variables as mediators in determining the continuous intention to use IoMT enabled the researcher to increase the predictive power of the model as the model now tackled not only the diffusion factors that affected the continuous intention to use IoMT but also the user behaviour factors (sections 5.14.3 and 6.3). Although the conceptualisation is not new but testing the usefulness of user behavioural aspects concerning the continuous intention to use IoMT when IoMT is diffusing still provided the researcher to show how the mediators could be manipulated to enable a greater influence of the exogenous variables on continuous intention to use IoMT. This is new knowledge as in the field of IoMT no such research outcome explains the variance of the dependent variable with regard to the determination of variables through an indirect relationship and the mediating effect of motivation and training to use IoMT has been found. There are similar research outcomes that have used mediators in regard to determining the intention to use IoMT but those research outcomes are based on such theories as the technology acceptance model in the context of other technologies but not diffusion of IoMT (e.g., Ntaukira et al., 2021; Al-Rahmi et al., 2019). The model developed in this research provides a way forward to alter and adjust both the exogenous variables and mediators to better understand and determine the continuous intention to use IoMT. This is new knowledge as hardly any research outcome is found in the extant literature that shows that continuous intention to use IoMT can be explained using the support of exogenous and other latent variables while IoMT is still diffusing, which have been explained in section 5.14.3

Furthermore, amongst the five constructs that aid in the diffusion of IoMT with built-in artificial intelligence as innovation, this research found that only three of them namely relative advantage, complexity and compatibility influence the continuous intention to use IoMT. Similar findings have been reported by other researchers who did not find trialability and observability as affecting continuous intention to use or acceptance or adoption of IoMT (e.g., Lu, 2021; Johnson et al., 2020; Kaur et al., 2020; Liao and Lu, 2008; Rogers, 2003). Thus, the results of this research confirm the current knowledge that shows that it is not essential to determine continuous intention to use IoMT using all the five DoI constructs. However, one difference that needs to be understood is that this research has found that the path motivation to continuous intention to use is influenced only by compatibility while the other path namely training to continuous intention to use IoMT is influenced by Relative advantage, complexity and compatibility. This implies that compatibility is the lone construct that aids the diffusion of IoMT and motivates healthcare professionals to continuously use IoMT. Similar results are reported by other researchers including Liao et al. (2021), Octavius and Antonio (2021), and Karahanna et al. (2006).
The implication is that it is compatibility which matters most as an independent variable that drives motivation, which in turn leads to continuous intention to use, a finding that shows that the other four diffusion factors are not useful. This is a new contribution to the body of diffusion of innovation field as compatibility alone can be the aiding factor in diffusion. While the findings in this research do not support the impact of relative advantage and complexity on motivation, at the same time, it finds support from other researchers including Bhat et al. (2021) and Elias and Walker (2017). Bhat et al., (2021) showed that there exists a positive relationship between compatibility, motivation and continuous intention to use IoMT while Elias and Walker (2017) showed that the construct healthcare practice compatibility acts as a determinant of behavioural intention to continued use of e-training by a healthcare professional. The reason why relative advantage and complexity did not find as significant determinants of motivation and continuous intention to use IoMT could be that healthcare professionals might have felt that relative advantage and complexity of IoMT are already built into the IoMT devices and have been addressed by the manufacturer of IoMT devices.

Next, the research has shown that relative advantage, complexity and compatibility are significantly related to training to use IoMT is new knowledge as most researchers have used training as a construct that is a subset of facilitating conditions and not a construct in its own merit (Wang et al., 2018; Venkatesh et al., 2012). Further, training in IoMT appears to be an essential mediator of the relationship between the three diffusion factors and continuous intention to use IoMT. This is a very new finding and indicates the extent to which training plays an important role in helping IoMT diffuse, leading to a better rate of adoption and continuous intention to use IoMT. To the knowledge of the researcher, no similar research results have been found in the extant literature that has discussed the mediating effect of training between diffusion factors depicted by diffusion of innovation theory and continuous intention to use IoMT. Thus, it can be argued that the dominating and mediating ability of training as a construct in the model during diffusion of IoMT driven by relative advantage, complexity and compatibility, leading to continuous intention to use or adopt is an important contribution to knowledge as current literature does not explain the role of training to use IoMT as a mediator in the relationship between DoI constructs and continuous intention to use IoMT. Details of how this can happen are provided in sections 6.3.8 to 6.3.10.

Another important finding is the negative relationship between relative advantage and training to use, which implies that the higher the relative advantage lower will be the requirement for training. While similar results are hard to find in the extant literature, some evidence is available that provides contradictory arguments. For instance, Putteeraj et al. (2021) point out that in the context of e-health, complexity surrounding the technology in regard to data handling may require rigorous training leading to a negative relationship between adoption and also a relative advantage. This implies that the higher the relative advantage, the lower the complexity and hence lower the rigour in training. These arguments show the inverse relation between relative advantage and training in technology. However, in another study by Mairura (2016) conducted in the context of automobile mechanics in micro and small enterprises in Kenya, RA was found to be directly linked to the training status of the mechanics with 82 percent of the mechanics agreeing to this fact. Amidst these contradictions, the results of this research show that the findings are similar to those of Putteeraj et al. (2021).

In addition, it can be seen that this research has found that motivation is a weak mediator while training to use IoMT adds to the determining power of the model. This implies that motivation contributes less to supporting the diffusion of IoMT embedded with AI when compared to training to use IoMT as an innovation. In practical terms, it can be seen that training to use IoMT devices will be a major contributor to supporting the continuous intention to use IoMT and more training could be helpful to determine the continuous intention to use IoMT. While literature shows that training drives the motivation of employees (Ozkeser, 2019), in the context of diffusion of IoMT or innovation like IoMT to determine motivation through innovation is an important finding of this research. In addition, researchers have used the concepts of training motivation (Carlson et al., 2000) and motivation training (Didion, 2017) that have implications for both motivation training. While these arguments underline the need to focus on both training motivation and motivation training, in this research what has been found is that training to use IoMT provides greater power to control the diffusion of IoMT and continuous intention to use IoMT than motivation. This finding is unique in the sense that motivation being a personal trait of a person, is less amenable to adjustment when compared to training. For instance, regarding IoMT, it can be seen that practical aspects drive motivation (Ho et al., 2021). Literature shows that companies need to provide training to the users of IoMT (Sodhro et al., 2021) regularly. Appendix 2 shows an example of the continuous training that a company dealing with wearables offers its customers. From these examples, it can be concluded that training is a more practical construct that could be used to motivate users of IoMT as well as enhance the continuous intention to use IoMT, which is an important contribution to knowledge.

It is important to note here that amongst the five exogenous constructs, four exogenous constructs (namely relative advantage, compatibility, trialability and observability) are found to have statistically significant relationships with them as evidenced by the covariance that exists amongst them. However, complexity does not have a statistically significant covariance with the remaining four exogenous variables. This implies that complexity as a stand-alone construct is able to act as a determinant of the continuous intention to use IoMT indirectly. The findings of this research closely align with that of Putteeraj et al. (2021) who found that complexity does not have a statistically significant correlation with compatibility, trialability and observability. This is a new finding in the field of IoMT and contributes to the body of IoMT usage knowledge. It implies that innovations need to be less complex for the users to continuously use those innovations. This could be a major factor that may need additional attention from the manufacturers of IoMT as wearable devices and other IoMT devices have been found to build in complex technologies that the users may not easily understand and learn. Finally, it can be seen that the association amongst the remaining four exogenous constructs show that trialability and observability have a strong association with relative advantage and compatibility. Any change in observability and trialability is thus likely to cause a change in relative advantage and compatibility of users of IoMT and thus motivation and training to use IoMT as well as continuous intention to use IoMT. This is a contribution to knowledge. Although both observability and trialability of IoMT did not have any statistically significant relationship with the other endogenous variables, it is seen those two exogenous variables can act on those endogenous variables through relative advantage and compatibility. Similarly, the association between compatibility and relative advantage indicates the possibility of relative advantage affecting motivation through compatibility. This another finding that can help manufacturers to control relative advantage and enhance motivation to use IoMT.

7.2.4. Contribution 4: Expansion of the application of DOI and behavioural theories to address continuous intention to use IoMT during concurrent diffusion of two innovations

This is related to the gap in the literature concerning the extension of the application of theories to explain the concurrent diffusion of two technologies and the continuous intention to use IoMT as a behavioural construct. It can be seen that on the one hand IoMT embedded with artificial intelligence technology is still diffusing, on the other this research has revealed that it is possible to control the five exogenous variables as well as mediators and moderators to enhance the continuous intention to sue IoMT even if the technology changes midstream through diffusion. This is a contribution to the body of continuous intention to use IoMT knowledge. This research thus provides a basis to understand which factos can be controlled, to what extent and in which direction.

However, it is important to recognise the support theories provide to gain an understanding of the contributions this research makes to knowledge, which is discussed next.

Foremost the research has applied the theory of diffusion of innovation to understand the intention of the healthcare professionals to continuously use IoMT embedded with another new technology which is artificial intelligence. Expanding the application of the theory of DoI to explain the continuous intention to use IoMT embedded with another new technology is a complex issue. DoI theory has been argued to help in the understanding of the diffusion of one innovation at a time and its adoption (Lin, 2021). However here two innovations are concurrently diffusing. According to Lin (2021) theory of DoI has not been applied so far to explain reuse of a technology or recurrent adoption of a technology that is diffusing. Thus Lin (2021) applied theory of DoI to explain the recurrent adoption of a diffusing innovation. The term recurrent adoption of a diffusing technology signifies the adoption of multiple versions of the same technology that is still diffusing, for instance the smart phones that are used in various sectors including healthcare (Lin, 2021). Thus, it can be seen that while diffusion of innovation theory has been widely applied by many researchers to explain the diffusion of one innovation at a time, that it can determine recurrent, continuous and reuse of technology was not known earlier. Expanding the application of the theory of DoI to explain the continuous use of IoMT with built-in artificial intelligence in this research is a contribution to the theory. The model developed for this research clearly demonstrates how the five DoI factors can help determine the continuous intention to use IoMT when IoMT is still diffusing.

Furthermore, the concurrent diffusion of two innovations like artificial intelligence based IoMT has not been explained in the literature using the theory of DoI (Aldhaen et al., 2021). The theory of DoI explains the user adoption rate of one innovation only at a time (Rogers, 2003). There could be more effects that could affect the diffusion and adoption two technologies that diffuse concurrently. Those effects need to be studied by applying a combination of theories other than DoI. From the results of this research, it can be seen that artificial intelligence based IoMT appears to be clearly welcome in this research, i.e., that concurrent diffusion of two technologies is welcomed. That is to say that the theory of DoI can now be applied to explain the diffusion of more than one technological innovation at a time. The results indicate that adopters have adopted an artificial intelligence based IoMT when it is still diffusing. Thus, this research has identified that the theory of DoI can be used to explain the conceptualization of concurrently diffusing innovations thereby creating a new avenue for studying and expanding the application of the theory. The result of such an expanded application DoI in this research shows that artificial intelligence as a new technology embedded in IoMT acts as a moderator of two relationships namely (relative advantage-training) and (complexity-training) in the research and aids the diffusion of IoMT by enhancing its relative advantage and training when it is complex. This is a contribution to theory.

Further, including complexity only three of the five DoI factors were found to be useful. Both trialability and observability were not found to be useful. Similar results are reported by other researchers (Martins et al., 2106; Lee & Cheung, 2004). This implies that there is no need to apply Rogers' theory of DoI, with all five factors as exogenous variables, to determine the continuous intention to use IoMT. This result is in agreement with those researchers who have reported similar outcomes (Martins et al., 2106; Lee & Cheung, 2004). However, this discovery needs to be read with caution because the research also found that complexity does not operate in unison with the remaining four DoI constructs while a relative advantage, compatibility, trialability and observability operate in combination. Although trialability and observability were not found to affect the continuous intention to use IoMT either directly or indirectly, those two constructs were found to have a strong association with both relative advantage and compatibility. This implies that both trialability and observability can influence the determinant's relative advantage and compatibility which in turn will affect continuous intention to use IoMT differently when both trialability and observability change.

Next, this research has advanced the application of both self-determination theory and theory of planned behaviour in explaining the behavioural aspects of the healthcare professionals in regard to continuous intention to use artificial intelligence based IoMT. Hardly any research has considered the application of self-determination theory and theory of planned behaviour to understand the influence of motivation and training to use IoMT on continuous intention to use. This research explained how self-determination of healthcare professionals and patients can enable motivation to be a mediator in the relationship between (compatibility-continuous intention to use IoMT) and provided the basis to establish a theoretical relationship between compatibility and continuous intention to use IoMT.

Similarly, with regard to training to use IoMT as a mediator in the relationships (relative advantage-continuous intention to use IoMT, complexity-continuous intention to use IoMT, compatibility-continuous intention to use IoMT) theory of planned behaviour provided the basis to establish a theoretical relationship amongst those relationships. TPB posits that users' behaviour is influenced by their intention to behave whereas the intention is influenced by attitude, subjective norms, and perceptions of behavioural control (Septiani & Ridlwan, 2020). It is commonly utilised to anticipate intention and behaviour in the context of technology adoption in the medical field (Bronfman et al., 2021; Hennings & Herstatt, 2019; Ifinedo, 2018). The evidence provided in the literature enabled the researcher to confirm the usefulness of applying the theory of planned behaviour to understand the usefulness of training as a mediator in the three relationships namely (relative advantage-continuous intention to use IoMT, complexity-continuous intention to use IoMT, compatibility-continuous intention to use IoMT). To the knowledge of the researcher, no research outcome has investigated the continuous intention to use IoMT as being influenced by training to use IoMT. Thus, this research contributes to the theory by expanding the application of the theory of planned behaviour to explain the importance of training to use IoMT as a mediator in the aforementioned relationships.

Finally, this research contributes to theory in explaining the use of artificial intelligence, novelty-seeking behaviour and age as moderators using the UTAUT model. While literature is replete with research outcomes that have used UTAUT as the basis to develop conceptual models in determining intention to adopt the behaviour of individuals (Turkes et al., 2020; Venkatesh et al., 2012), this is research could be one of those first efforts that have applied the concept of UTAUT in developing a conceptual model where moderators find importance. UTAUT provided the basis to identify artificial intelligence as the moderator of the three relationships namely (relative advantage-training to use IoMT, complexity- training to use IoMT, compatibility- training to use IoMT). It also provided the basis to explain how as a moderator artificial intelligence awareness was found to concurrently diffuse alongside IoMT although as a supporting technology). Similarly, the concepts of age and novelty-seeking behaviour were established in the conceptual model with the direct support of the UTAUT which is supported by Venkatesh et al., (2012). Thus, this research has expanded the application of the concepts of UTAUT in understanding the moderating behaviour of the three moderators conceived in this research. After discussing the theoretical contributions to the body of the behavioural intention of the healthcare professionals to continuously use IoMT literature, the next section identifies the contribution to practice.

7.3. Contribution to Practice

There are a number of challenges faced by healthcare professionals in providing the best patientcare using advanced technologies. IoMT is an advanced technology and researchers continue to raise concerns about its practical use of IoMT. Concerns like enabling improved patient comfort, cost-effective medical solutions, quick hospital treatments, and even more personalised healthcare are becoming a challenge (Razdan & Sharma, 2021). These challenges are both patient-centric and organisation driven. Implementation of IoMT is becoming mandatory as without this many healthcare organisations are not able to meet the demand of the industry. Further demands are being put forward by patients and organisations on the healthcare professionals like improved clinical efficiency, an increase in the requirement for home monitoring after discharge of the patient, fitness wearables, infant monitoring, an increase in the use of biometric sensors and wearables, monitoring during sleeping and use of brain sensors (Giri et al., 2019). In addition, security and privacy concerns, training for healthcare professionals, awareness creation, accuracy, reliability, efficiency and effectiveness of using IoMT have all caused serious stress on the healthcare professionals and the continued use of IoMT (Yaacoub et al., 2019). The outcome of this research has provided some support to overcome many of the aforementioned practical problems.

7.3.1. Contribution: To healthcare policy

Foremost, this contribution is about the gap in the literature concerning the policies a healthcare organisation needs to adopt while implementing IoMT in the organisation. It is clear that many of the problems arise out of continuously advancing technology which requires awareness amongst the healthcare professionals. This research has highlighted the diffusion of two complex technologies and the lack of awareness about those technologies is a major problem amongst healthcare professionals. For instance, awareness about artificial intelligence embedded in IoMT and its usefulness in providing the best patient care is expected to support the continuous intention to use IoMT. Especially awareness about AI during the early part of the diffusion of IoMT and training in AI-based IoMT become necessary for users to understand how the technology is able to support them and how those technologies can be used and reused. Without this clinical efficiency and accurate measurements by healthcare professionals using IoMT will become a challenge. Thus, it can be seen that when IoMT is implemented, it becomes important for the organisations to organise regular training and awareness creation programmes for the effective use and delivery of healthcare. This research has provided evidence indicating the need for organisations to adopt this procedure as a policy.

7.3.2. Contribution 2: To IoMT implementation in healthcare organisations

Furthermore, with regard to the five important diffusion constructs on which of the five constructs there needs to be an emphasis while practically implementing the continuous intention to use IoMT, specific knowledge has been brought out in this research that could be used to control those constructs. For instance, the relative advantage of IoMT needs to be practically highlighted through appropriate training. If the relative advantage of IoMT embedded with AI is not perceived by the healthcare professionals then despite the continuous use of IoMT, the users will not be able to exploit the advantage of the latest innovation. Thus, there is a need to link the relative advantage to the training aspects and explain to the healthcare professionals the importance of utilising the various benefits offered by the latest technology. For instance, artificial intelligence based IoMT can provide many benefits to healthcare professionals in terms of monitoring the healthcare of patients by providing an intelligent interaction between patients and the devices. Deploying such devices requires healthcare professionals to be fully trained. Thus, a training department that exclusively takes care of the healthcare professionals' needs to gain knowledge about the devices becomes imminent in every organisation. This must become a policy of every organisation to have an exclusive training department that regularly takes care of the requirements of the healthcare professionals' needs when they continuously use IoMT.

Next, the complexity of IoMT has a major bearing on the security of patients' data, accurate use and implementation of the devices, and providing the best and most efficient patientcare. This research has shown that complexity affects training with increased complexity calling for increased training. It is clear from the results of the research that the higher the complexity, the higher the requirement for training. So continuous intention to use IoMT will depend upon how complexity is addressed by the trainers. For instance, many wearables have data security issues. Such security issues can jeopardise the patients and compromise their privacy. The healthcare professionals need to be provided with real-time examples of how security threats need to be understood and how vulnerabilities need to be tackled. This is a complex issue. There has to be a close interaction between technical experts and healthcare professionals to deal with this situation. There must be a policy in every healthcare organisation to have standby technology experts who understand the technical pitfalls and have the knowledge of remedial measures and can support the healthcare professionals. Despite the best training, it is possible that certain technical malfunctions or errors occurring in IoMT are not understood by a healthcare professional and there is a need for a mechanism for a channel in healthcare organisations for constant and continuous interaction between the experts and users of the healthcare.

One of the challenges raised by the complexity is that technology devices may not be fitting into the medical context in which they are used. In such situations, users would be able to report concerns if they were given adequate training so that technology developers would be able to improve the performance, design, and usage instructions, as well as make it more consistent with the needs of the clinicians. Furthermore, the consequences of increasing technological complexity need to be borne in mind by manufacturers of IoMT. The complexity in IoMT is linked to, a number of times, a lack of training facilities the result users are left in the lurch and are clueless about how to utilise those technologies. So IoMT manufacturers and healthcare providers must provide adequate training to understand the new technology as well as how to use them properly. This is an important practical implication that arises from this research.

Another important practical need is the compatibility of IoMT embedded with AI. Compatibility is critical for user acceptance and diffusion; when users see that a product is compatible and fits for their lifestyles and tastes, they are more motivated and inclined to utilise it without hesitation. This is confirmed by the results of this research. For instance, if the compatibility of wearables is affecting their implementation in terms of interoperability of those wearables with other devices, then the healthcare professionals would not use the wearables. Therefore, manufacturers of wearables must provide adequate education and training to healthcare professionals if those healthcare professionals' intention to use and reuse the devices has to be ensured. Thus, it can be seen that compatibility not only indicates the need to provide adequate training to users of IoMT but also motivate them with appropriate education and awareness programmes. This in turn will ensure that healthcare professionals are able to connect the devices seamlessly with other equipment leading to better interoperability of the devices and provision of the best healthcare to patients. As important practical implications, it is possible to posit that while creating devices or applications for patients or healthcare professionals, IoMT manufacturers or developers must focus on the user's needs and the device or application's compatibility. As far as healthcare organisations are concerned, policymakers should make sure that any purchased device is compatible with the needs of the users which includes both the patients and healthcare professionals.

7.3.3. Contribution 3: Behavioral aspects during implementation of IoMT

This is concerning the behavioural aspects that need to be implemented in the healthcare organisation to ensure continued usage of IoMT devices. It is important to note that when systems or devices are compatible, training costs are also minimised. If all of the devices and software in use come from the same vendor, common instructions and processes will apply across the board, making it easier for users to be educated and get accustomed to those devices. As a result, healthcare organisations should emphasise the requirement for compatibility of the IoMT devices at the time of purchase in order to streamline integration with the existing systems as well as enable better training for the users which is expected to enhance the motivation of the users.

The results of the research have shown that both motivation and training as behavioural constructs are important to integrate as a policy while implementing IoMT failing which there could be usage issues. Continuous intention to use IoMT promises organisations, patients and healthcare professionals to provide seamless, consistent, efficient and the best patientcare. Regardless of the frequent changes that may affect the usage of IoMT devices, in patientcare there needs to be a complete diffusion of a technology which needs to support patientcare over a reasonable period of time. In order to use or reuse technology the users, behavioural aspects are very important. This research has shown that diffusion alone cannot lead to continuous intention to use IoMT but there is a need to understand user motivation and training needs that support not only complete diffusion of technology but also continuous use of that technology. Thus, it can be seen that the healthcare organisations need to support users of IoMT with regard to their motivation by continuously supporting their needs and wants. Towards this, it is important that there is a coordinated effort between the manufacturers of IoMT devices and the healthcare organisations to analyse the user requirements like compatibility, relative advantage and complexity of the IoMT devices so that users are motivated, and their training is not complex. As shown by this research motivation and training act as important mediators that need to be tackled by healthcare organisations to ensure continued usage of IoMT. It should be a matter of concern for the human resource departments in healthcare organisations who devise policies to motivate users by providing appropriate support in terms of awareness sessions, seminars, workshops and training regularly on IoMT devices and their usage.

7.3.4. Contribution 4: To practical issues concerning Continuous Intention to use IoMT

The model developed for this research provides the practical basis on the important factors that need to be focused on while implementing IoMT. For instance, this research has shown that DoI as theory has been used to determine the rate of adoption of artificial intelligence based IoMT using the new concept of concurrent diffusion of two technological innovations namely artificial intelligence and IoMT. The conceptual framework developed for this research provides an opportunity for researchers, consultants and academics to investigate behavioural aspects of healthcare professionals and understand how those professionals will act when new innovations appear in the market. Decision-makers can now know that focus should be more on the relative advantage, complexity, compatibility, motivation and training to ensure continuous and predictable use of IoMT. Finally, healthcare professionals are the most important beneficiaries of this research. The research shows that continuous use of technology could be beneficial although changing over to novel innovations could be useful at times. However, such changeovers should be considered by taking into account the diffusion dimensions namely relative advantage, complexity and compatibility of the new innovation. In addition, the healthcare professionals should be supported with training by the manufacturers of those innovations and find motivational support to change over to the new innovation. In addition, healthcare professionals look for more supporting technologies like artificial intelligence that make their practice more advanced, to date and enable them to provide the best care to the patients. After discussing the contributions to practice, this research discusses the limitations of research.

7.4. Limitations of Research

This research embarked on studying the central issue of the continuous intention to use IoMT in the context of healthcare professionals working in hospitals when IoMT is still seen to be diffusing. During the study, the researchers came up with unique contributions to knowledge and theory. One such contribution was the extension of the application of the theory of DoI to the diffusion of artificial intelligence based IoMT, which comprises two innovative technologies. DoI theory has not been applied to research that investigated the diffusion of more than one innovation at a time while this research studied the concurrent diffusion of two innovative technologies namely IoMT and artificial intelligence so far. Since there is no similar research outcome found in the literature that has investigated the application of the theory of DoI to explain the concurrent diffusion of two different innovations, with the sole exception Aldhaen et al., (2021), comparing the results of this research was difficult. More research in this area is therefore needed to validate the research outcomes.

This research applied the theory of diffusion of innovation and used the five dimensions namely (relative advantage, complexity, compatibility, trialability and observability as the determinants of continuous intention to use IoMT. However, the research showed that two of the five dimensions namely trialability and observability were found statistically insignificant relationship with the continuous intention to use IoMT. This could be due to some reasons, one of them being that both trialability and observability are considered to be not solely related to the innovation diffusion process (Martins et al., 2106). Considering the fact that this research has investigated the continuous intention to use IoMT as a dependent variable by the exogenous variables identified by DoI and mediated by motivation and training. It is quite possible that the mediators could have played a role in the lack of significance of the two dimensions of DoI. For instance, in this research the dimensions of trialability and observability were not linked to training because training as a construct is considered to encompass both training and observability (Pereira & Wahi, 2017; Singer, 2004). Thus, the results of this research indicate the lack of statistical significance with regard to the relationship between trialability and observability on the one hand and motivation on the other need should not be viewed in isolation as similar arguments are found in the literature.

Further, the above arguments could also be applied to the lack of statistical significance of the relationship between the four dimensions of DoI namely relative advantage, complexity, trialability and observability on the one hand and motivation on the other. The limitation related to two dimensions of DoI namely trialability and observability as not having statistical significance has been highlighted above. However, the lack of statistical significance found in analysing the relationship between relative advantage and complexity on the one hand and motivation on the other can be a limitation. For instance, it is possible relative advantage of IoMT embedded with artificial intelligence could be considered an advantage for motivating healthcare professionals. Similarly, complexity of IoMT embedded with artificial intelligence could be a demotivating factor if healthcare professionals feel that IoMT embedded with artificial intelligence is very complex to use. This aspect may need to be understood through further investigations.

The other limitations of this research include the following. This research has developed a conceptual model with two concurrently diffusing technologies. While applying the theory of DoI, the researchers assumed that mediators could be useful in determining the intention of healthcare professionals to continuously use IoMT during its diffusion and chose motivation and training to use IoMT as the mediators. These two constructs are behavioural aspects. However, there are other behavioural aspects suggested by researchers that could be considered to be conceptualised as mediators including workload and stress (Malik et al., 2021; Baskaran et al., 2020; Agboola & Olasanmi, 2016), language barrier (Kariuki & Okanda, 2017; AL-Hadban et al., 2016; Folaranmi, 2013), culture (Krey, 2020; Wickramasinghe, 2018; Alshare et al., 2011), social environment (Yang Meier et al., 2020; Wickramasinghe, 2018), Trust (Arfi et al., 2021; AlHogail, 2018; AlHogail & AlShahrani, 2018) and usage of IoMT. However, considering the scope and timeframe of this research only two mediators namely motivation and training to use IoMT were investigated which yielded results that show both mediators play an important role in worthy relationships (relative advantage-training to use IoMT, complexity-training to use IoMT, compatibility- training to use IoMT).

However, the conceptualisation of artificial intelligence as a moderator of the relationships (relative advantage-training to use IoMT, complexity- training to use IoMT, compatibility-training to use IoMT) could be too narrow. Artificial intelligence is a dominating invention. It may be necessary to look at it as a determinant of continuous intention to use IoMT in place of its conceptualisation as a moderator. It is likely a different result could have been achieved. Similarly, the other two moderators namely age and novelty-seeking behaviour of healthcare professionals were also found to have no significant effect on the relationships (motivation-continuous intention to use IoMT) and (training-continuous intention to use IoMT). This could be a limitation as novelty-seeking behaviour is shown to be related to intention to adopt behaviour in the literature by some researchers (Wong et al., 2019). The reason for this result could have been the fact that artificial intelligence based IoMT could have been considered an essential tool required to improve current healthcare practices and provide the best patientcare regardless of the fact that it is a novelty or not. It is possible if novelty is conceived as either a mediator of the relationship between diffusion dimensions and continuous intention to use IoMT or a determinant of continuous intention to use IoMT, the results could have been different. Similarly, age was found to be an insignificant factor. As IoMT is now pervading all age sections of a population that could be grouped under different age categories it is possible that respondents might have considered age as an insignificant factor. IoMT devices are now used as wearables by people under different age groups and are a common sight in the world. If a specific age group of healthcare professionals having a particular number of years of experience in using IoMT were to be approached again, then perhaps the results could be different.

Finally, this research was conducted based on data collected from various types of healthcare professionals through a cross-sectional survey. If the research were to be conducted targeting a specific set of healthcare professionals like physicians or nurses, the results of this research could be different. After discussing the different limitations of this research, the next section recommends some areas for consideration by researchers for future research.

7.5. Recommendations for Future Research

As a central issue, continuous intention to use IoMT has hardly been investigated by researchers when it is still diffusing. This research is one of the few examples that could be found that has investigated continuous intention to use IoMT and was conducted in specific contexts. In order to validate the research outcomes provided in this research further research is needed. Therefore, more research is needed in multiple contexts for instance in the context of particular healthcare segments, specific healthcare professionals, different geographical locations and specific age groups. This will throw up new knowledge about the intention of particular healthcare professionals to continuously use IoMT.

Next, future research is recommended by conceptualising artificial intelligence as a determinant instead of a moderator. The impact of artificial intelligence as a determinant may have a different effect on continuous intention to use IoMT. Similarly, conceptualising novelty-seeking behaviour as a mediator in a similar fashion to that of motivation and training could provide new ideas on the influence of novelty-seeking behaviour on continuous intention to use IoMT. This could also produce different results with regard to the significance of the influence of complexity, trialability and observability on continuous intention to use IoMT.

Further, more research is needed to understand the concurrent diffusion of two technologies applying DoI, which is until now applied only to understand the diffusion of a single innovation linked to the rate of adoption. The current research has produced useful results to understand how two concurrently diffusing innovative technology could be conceptualised. Further research could build on the outcomes of this research to reveal deeper knowledge. Additionally, the conceptual model developed for this model could be tested with different mediators including workload and stress, language barrier, social environment and trust. These mediators could produce results that could be different from those of this research. Finally, in this research cross-sectional data was used to investigate the relationship between the latent variables. Longitudinal data could provide a deeper insight into the intention of the healthcare professionals to continuously use IoMT.

7.6. Lesson Learned and Personal Reflection

The main purpose of this research was to examine and determine the continuous intention to use AI-based IoMT technology when it is still diffusing. Hence, the investigation revolved around the diffusion factors affecting the continuous intention to use IoMT by healthcare professionals. The target population studied was the healthcare professionals working in the healthcare sector in the Kingdom of Bahrain.

Since AI-based IoMT devices and applications are new, smart, disruptive and fall under emerging technologies and have effectively transformed the healthcare sector recently, I started my journey knowing very little about them, including aspects like the primary benefits and limitations of their use and how they are implemented. But slowly I started to pick up knowledge about the various aspects concerning the AI-based IoMT devices and applications and what is the current status of research on their use. I reviewed the literature thoroughly and gained wider knowledge about my subject which was by itself a new experience. In the process, I learned about a few theories concerning my central concept, which helped me to construct my research framework and the research structure that goes with it. My understanding expanded as I progressed through the stages of the research and read a huge number of empirical research publications and peer-reviewed articles. I gained a better understanding of theoretical frameworks and their significance to research outcomes as part of my investigation in the core area of continuous intention to use AI-based IoMT. Developing an appropriate research framework and integrating with my research was a difficult step and reaching the final shape of the research model was challenging. I had drawn many models and all of them failed until I developed the most appropriate model for my research with the support of my supervisor as well as the profound knowledge, I gained from reading empirical studies.

During the COVID 19 outbreak data collection was a problem as it was extremely difficult to communicate with hospitals and clinics. Unexpected emergencies caused by COVID 19 and the prohibition on visits to the hospital by anyone other than those having an emergency, was a major challenge I faced throughout my PhD journey. I relied on making phone calls, sending emails, and following up with the departments concerned subsequently to access potential participants. After continuous and exhausting hardwork, I got consent from the hospital directors to distribute the survey instrument. I was then able to gather data from 354 healthcare professionals from public and private hospitals, health centres, and clinics in Bahrain. The survey instrument was posted online, and the link was distributed by official emails and social media channels. The total number of responses received met the sample size requirements. To analyze and test the hypothesis, I used SPSS and AMOS to perform the descriptive statistics, instrument reliability and validity analysis, structural equation modelling and many other tasks.

Learning SPSS and AMOS from scratch was not easy at all and was a big challenge for me as I had to set aside time for learning by attending online workshops and watching YouTube videos. This helped me gain a thorough understanding of how to use those tools and practice using both the tools. Participating in the university's annual conferences and publishing in 3-star journals benefited me as a researcher as well as helped maintain a positive relationship with academic supervisors which I learned is a very important step for a PhD candidate to be successful and complete the PhD journey in order. Monthly meetings, constant advice and comments from my supervisors enhanced my capabilities and research skills, especially in writing and preparing me for the defence of my thesis. Academic thinking was a very different experience, especially when it comes to justifying, interpreting and referencing appropriate literature and introducing new ideas and arguments. My PhD experience has taught me several things, but the most significant lessons I've learned are patience, determination, commitment, and time management. These four qualities have changed my life and helped me become a researcher. Despite the challenges, I had an enjoyable learning experience at the University of Bradford. This PhD study journey allowed me to understand how to conduct holistic research in academia and gain knowledge on different topics and practical aspects that are required to conduct good research.

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Appendix 1

Telemedicine Examples

Type	Task	Reference
Tele- nursing	Telenursing allows nurses to interact remotely with patients by answering questions, consulting and suggesting medication by using information and communication technology tools involving voice and video communication including online portals and phones. Telenursing has achieved remarkable growth rates in many countries and helps to solve the issue of shortages of nurses in addition to saving time and travel costs for those patients who cannot afford to pay the cost of travel or attending the hospital physically, for instance, the elderly people.	(Rawat, 2018) (Arnaert & Delesie, 2001; Souza-Junior et al., 2016)
Tele-pharmacy	Tele-pharmacy provides pharmaceutical care using telecommunications to deliver medicines to patients' locations without a direct connection with the pharmacist. Tele-pharamcy uses videoconferencing and teleconferencing to observe patients and drug therapy in addition to controlling and counselling for refilling prescription drugs.	(Poudel & Nissen, 2016; Baldoni et al.,2019) (Win, 2017; Le et al., 2018)
Tele-dermatology	In 1995, the term teledermatology was known through scientific publications when two dermatologists Perednia and Brown coined the term. Tele-dermatology is mainly used to share and exchange medical information concerning skin and hair to be able to discover cases of early stages of skin cancer by conducting tests, diagnosis, seeking medical advice or receiving treatment using data communication, audio, and visual communication. Tele-dermatology is very cost-effective since it is done over a distance. It saves time and effort for patients to visit dermatologists.	(Perednia & Brown, 1995) (Thomas & Kumar, 2013) (Warshaw et al., 2011)
Tele- cardiology	Telecardiology is one of the successful telehealth tools that are cost-effective and combines cardiology with technology to offer cardiac care by providing true information with medical instructions. Telecardiology allows the remote specialist to interpret the recordings of electrocardiographs (ECG) to be able to read and transmit them using phone transmission and wireless connection.	(Backman et al., 2010)

		(Hsieh et al., 2013)
Tele-dentistry	Tele-dentistry allows patients who suffer from dental or oral problems to receive virtual advice, consultation or treatment through information and communication technologies instead of real physical communications between patients and dentists involving visiting clinics. It is one of the innovative real-time technologies through which the dentists can share and exchange dental x-rays with patients. In addition, it reduces the cost of travel, and saves time and effort on the part of patients.	(Jampani et al., 2011) (Arora et al., 2019)
Tele- surgery	Telesurgery is also called remote surgery, which allows the surgeons distantly located from the patients, to perform robotic surgeries in real-time. It relies on information and communication technologies and robots that are handled and controlled by surgeons as though the surgeons are performing surgeries at the hospital in person. Telesurgery uses video communication transferred as real-time videos and medical imaging. It provides the opportunity for the surgeons to share their expertise worldwide in real-time, making the physical distance between the surgeon and the patient immaterial.	(Choi et al., 2018) (Natarajan & Ganz, 2009)
Tele- psychiatry	Telepsychiatry is one of the telehealth tools which is undertaken in real-time by using telecommunication technologies including videoconferencing to enable consultation between patients and psychiatrists, and to facilitate diagnosis, treatment, educational clinical programs and follow up meetings. Telepsychiatry is considered one of the effective tools to help patients who are suffering from depression, and agoraphobia. and post-traumatic stress disorder.	(Deslich et al., 2013) (Chakrabarti, 2015)

Appendix 2

List of IoMT devices and their descriptions

IoMT device	Task	References
Remote Patient Monitoring	Patient monitoring is one of the real-time devices and cost-effective tools; consists of wearable devices with a fixed sensor; observes daily the health status and vital signs of patients who suffer from chronic diseases; notifies clinicians about problems.	Malasinghe et al. (2019); Gómeza et al. (2016); Malathi and Preethi (2019)
Connected Inhaler	Controls patient conditions and provides smart solutions to those patients encountering asthmatic symptoms and prevents asthma attacks and reduces healthcare costs; electronic monitoring measures medication adherence; helps clinicians to track patients' conditions and inform the patient if the use of inhaler is required or not.	Kikidis et al. (2016) Blakey et al. (2018) Mohammadi (2019)
Heart Rate Monitoring	Monitor sports men and women while they are training and carry out exercises such as treadmill exercises, cycle ergometers and endurance exercises to assist them to get trained at the pre-planned intensity. HRM associated with IoT applications is being used nowadays in hospitals to gather heart rate data by recording the pulses and heart rate using sensors that analyse the heartbeats, pulses and temperature of patients.	O'toole et al. (1998) Achten & Jeukendrup (2003) Manisha et al. (2016)
Smart Watches for Depression	Used to monitor depression. For example, a smartwatch based on artificial intelligence and machine learning detects the level of depression and saves it in the cloud. The smartwatch tracks depression levels and suggests solutions for those who suffer from depression by collecting and analysing behavioural data of the patients.	Hickey et al. (2020) Vaseem and Sharma (2019) Wang et al. (2018)
Smart continuous glucose monitoring (CGM) & insulin pens	The smart CGM is a real-time monitoring device that aids patients with diabetes to observe their blood glucose levels and concentration	Cappon et al. (2019); Umpierrez and Klonoff (2018); Cappon et al. (2017); Koseoglu and Pektas (2018)
Blood coagulation testing	Allows patients to check the blood clots level and how quick and steady it is through a self-test that assists patients to remain with their therapeutic range. It reduces the risk of having blood clotting disorder, brain stroke as well as bleeding problems.	Mishra & Rasool (2019) Yao et al. (2018)
Ingestible sensors	Ingestible sensors (pills) help in controlling the intake of medicines of such patients. It works when the pill dissolves in the patient's stomach and gives a notification which is linked to a wearable used by the patient.	World Health Organisation (2003); Frias et al., (2017)
IoT connected contact lenses	Help in treating the patients who suffer from presbyopia and cataract. Also detect many diseases such as diabetes. Assists doctors to detect the dangerous disease called glaucoma that leads to blindness.	Chou & Legerton (2017); Kang, et al. (2018); Xu, et al. (2016)

Appendix 3

Strengths and weaknesses of TPB

TPB proposed by Ajzen (1985)			
Strengths	Authors	Weakness	Author/s
It is a broader model as compared to TRA	Ajzen (1985)	The theory develops a sense of falsehood to people due to positive attitudes towards habits, which the end might be costly to some individuals.	Lada (2009)
The theory has gained considerable support in social science, IT literature and other realms about the prediction of behaviour	Mykytyn and Harrison (1993).	The research concepts of this theory are not easy to measure and define.	Olushola and Abiola (2017)
This theory has been proven successful in terms of comprehending individual acceptance as well as in the application of various technologies.	Harrison et al., (1997)	The theory’s independent variables tend to experience multi-collinearity.	Olushola and Abiola (2017)
The theory helps one to link personal beliefs and behaviours.	Montebello (2019)	TPB has been criticised to be too logical and rational to accept, especially regarding human behaviour and does not account for cognitive and affective processes that are known to bias human judgments and behaviour completely.	Ajzen (2011)
TPB is a suitable theory for assessing factors which influence the sharing of knowledge.	Ryu et al. 2003; Lin and Lee (2004)	The model’s attributes of behavioural intention to use technology are limited to the individual units of analysis rather than organisational level.	Wickramasinghe (2016)
The theory enhanced the predictability of intention in many related studies in the healthcare domain.	Guest and Namey (2014)	TPB doesn’t consider factors related to personality, cultural and demographic factors.	Sharma and Kanekar (2007)
TPB gives an easy and efficient framework to be used by the investigation of an individual’s intent to perform context-specific actions.	Russo et al (2015)	TPB focuses only on rational thoughts and does not take irrational thoughts or fears into consideration.	Sharma and Kanekar (2007)

Appendix 4

Strengths and weaknesses of DoI

DoI proposed by Rogers (1995)			
Strengths	**Authors**	**Weakness**	**Author/s**
Provides a new lens for investigating the appeal and the spread of any fast innovation.	Scott and McGuire (2017)	Ignores the cultural practices of the target healthcare providers.	W.H.O (2017)
DoI theory is considered a beneficial systemic framework for explaining either adoption or non-adoption of new technologies.	Sana'a (2016)	More concerned with adopters than with the social framework in which dispersion occurs.	Hazelman (2017)
Able to predict the bahavioural intention to use IoMT of various varieties of innovations among unique kinds of people and contexts.	Al-Tarawneh (2019); Wolfe (1994)	Several details are related to cost and special facilities have been ignored.	Al-Tarawneh (2019); Downs and Mohr (1976)
Clear understanding of consumer innovation and behavioural intention to use IoMT.	El Mustapha (2018)	Disregards social elements, including how a social device may want to affect or foster the behavioural intention to use IoMT of recent improvements.	Al-Tarawneh (2019); Rogers (1976)
Provides knowledge on how innovations diffuse and end up being adopted by individuals and organisations.	El Mustapha (2018)	Knowledge gap on cultural characteristics.	El Mustapha (2018)
Provides a set of factors that could be used to understand the innovation behavioural intention to use IoMT decision of users of the innovation.	El Mustapha (2018)	How sociocultural factors influence the innovation-diffusion process is not clear.	El Mustapha (2018)
Theory allows for feedback collection from healthcare providers who accept the new technology.	Laius et al. (2018)	DoI has weaknesses in predicting individual and organisational behaviour.	Ward (2013)
Can be used to understand continued usage or reuse or repeated use of an innovation	Zhang et al., (2015)	DoI works at the level of the firm and not for the level of the individual.	Oliveira and Martins (2011)
DoI theory is a macro-level theory in which developments at the group level are implemented to improve the health behaviour of a society	Lien and Jiang (2017).	It has less explanatory power and is less useful for result prediction.	Taherdoost (2018); Hazelman (2017)
		Insufficient attention is paid to the characteristics of innovation and how they evolve over time.	(Wolfe, 1994)
		The form of knowledge used in innovation spread is further complicated by the difference between simple adoption (replication) and reinvention (adaptation).	Nutley et al, (2002)

Appendix 5

Strengths and weaknesses of UTAUT

UTAUT proposed by Vankatchet al. (2003)			
Strengths	Authors	Weakness	Author/s
The model and theory have been applied and adopted by many technology-based services such as self-service technologies.	Al-Tarawneh (2019); Martins et al., (2014); Al-Qeisi and Abdallah (2013); Riffai et al., (2012); Yu (2012); Abu Shanab et al., (2010)	The study is simple and does not embrace sophisticated or complex technologies.	Al-Tarawneh (2019); Chiu et al. (2010)
It has a very high prediction influence.		The theory views technology more from the employees' perception.	Al-Tarawneh (2019); Venkatesh et al. (2012)
The UTAUT model has the advantage of taking into account the function of several moderating variables, such as gender, age, experience, and voluntariness of use	Venkatesh et al. (2003)	Difficult to generalise the outcomes as the majority of research efforts have been accomplished in intentional conditions of usage rather than compulsory use.	Al-Tarawneh (2019)
UTAUT has been used to understand user adoption of a variety of information technologies that are used in different sectors such as health, banking, mobile etc.	Alwahaishi and Snásel (2013)	UTAUT assume that the use of the system is always voluntary, which in most scenarios is not always the case.	Sana'a (2016)
		Bias across cultures.	El-Masri and Tarhini (2017)
		UTAUT only utilises a single IS for research.	Chang et al. (2007)
		UTAUT is tough to apply due to its complexities.	Bagozzi (2007)
		It's difficult to draw conclusions from data analysis and to extrapolate the result.	Ye et al. (2008); Wang and Shih (2009)
		The weakness of UTAUT is its inflexibility to respond to multiple and different contexts.	Al-Gahtani et al. (2007)
		Does not address reuse intentions.	Wang et al. (2021)

Appendix 6

Prior studies used for developing the survey instrument

Item code	Variable/Type of variable/Items	Item adapted from
	Relative advantage of IoMT - Independent	Savoury (2019); Al-Rahmi et al. (2019); Moore and Benbasat (1991)
RA1	Using an IoMT application enables me to complete tasks faster.	
RA2	Using an IoMT application improves the quality of work I do.	
RA3	Using an IoMT application makes it easier to do my job.	
RA4	Using an IoMT enhances my effectiveness on the job.	
RA5	Using an IoMT gives me greater control over my work.	
RA6	Using an IoMT increases my productivity.	
	Complexity of IoMT - Independent	
CPX1	The use of IoMT requires a lot of mental effort	Oliveira et al. (2014)
CPX2	The use of IoMT is frustrating	
CPX3	The use of IoMT is too complex for business operations	
CPX4	The skills needed to adopt IoT are too complex for employees of the firm	
	Compatibility of IoMT - Independent	
CMP1	Using an IoMT is compatible with all aspects of my work.	Savoury (2019); Al-Rahmi et al. (2019); Moore and Benbasat (1991)
CMP2	Using an IoMT is completely compatible with my current situation.	
CMP3	I think that using an IoMT fits well with the way I like to work.	
CMP4	The use of IoMT is fully compatible with the value system of my workplace	
	Trialability of IoMT - Independent	
TRI1	I have had a great opportunity to try different IoT applications.	Al-Rahmi et al. (2019); Moore and Benbasat (1991)
TRI2	I am aware where I can go to try out many uses of IoT.	
TRI3	Before deciding on whether to use IoT applications, I was in a position to properly try them out.	
TRI4	I was permitted to use IoT applications on a trial basis over a long and sufficient period of time to see what it can do	
	Observability of IoMT - Independent	
OBS1	I have seen what others do while using IoMT.	Al-Rahmi et al. (2019); Moore and Benbasat (1991)
OBS2	In my organisation, one sees IoMT applications used in different units.	
OBS3	I have seen the use of IoMT outside my organisation	
OBS4	I have had many opportunities to see IoMT being used	
	Motivation to use IoMT - Mediating	
MOT1	My job requires me to do it	Guay et al. (2000); Vallerand et al. (1989)
MOT2	I think it is interesting	
MOT3	I feel good when using it	
MOT4	I think that this activity is good for me	
MOT5	I believe that this activity is important for me	
	Training to use IoMT - Mediating	
TRN1	My performance was satisfactory on the IoMT application training	Alias et al. (2019); Saks and Haccoun (2007), and Noe (2010)
TRN2	I was able to achieve the objectives of IoMT application training	
TRN3	I could learn as much as possible from the training on IoMT	
TRN4	I was able to benefit from the training on IoMT	
TRN5	The training on IoMT significantly added to my knowledge	
	Continuous intention to use IoMT - Mediating	
CI1	Given the chance, I intend to use IoMT applications	Venkatesh (2000);
CI2	I am willing to use IoMT applications in the near future	
CI3	I will recommend IoMT applications to others	

CI4	I will continue using IoMT applications in the future	Venkatesh et al. (2012)
	AI Awareness - Moderating	
AWS1	I receive enough information about AI in from service provider of IoMT.	Al-Somali et al. (2009)
AWS2	I receive enough information about the benefits of AI integrated in IoMT.	
AWS3	I receive enough information of using AI integrated in IoMT.	
AWS4	I am aware of the education/training programs about using AI integrated in IoMT offered by the service provider	
AWS5	I have come across campaigns by the service provider about using AI integrated in IoMT	
AWS6	I am aware of the importance of ethics (e.g., ensuring security and privacy of user data) while using AI integrated in IoMT.	
	Novelty seeking - Moderating	
NS1	While using IoMT, I am always seeking new ideas about IoMT	Mehrabian and Russell's (1974); Dabholkar and Bagozzi (2002)
NS2	While using IoMT, I am always seeking new experience about IoMT	
NS3	I do not prefer an unpredictable way while using IoMT but prefer the one without any change in my routine use of IoMT.	
NS4	I like to continually change my way of dealing with IoMT activities.	
NS5	I do not like meeting healthcare service providers who have new ideas about IoMT.	
NS6	I like to experience novelty in IoMT	
Age	**Age - Moderating**	

Appendix 7

Introductory letter to the participants in the research

Dear Sir or Madam,

I am doing my PhD in Bradford University. The area of my research is adoption of internet of medical things in the field of healthcare with a focus on healthcare service providers. The title of my research is "Investigation into the factors affecting the relationship between diffusion of internet of medical things (IoMT) as an innovation and continuous intention of healthcare professionals to use IoMT". The research aims at understanding the various factors that enable the diffusion of IoMT applications, an innovation that is expected to have significant impact healthcare professionals on their continuous intention to use IoMT. Data for this research is required to be collected through the survey questionnaire developed for this purpose and enclosed with this note.

The survey is self-administered and has been developed, using a predefined (single response) scale that facilitates easiness in completing the questions. Since the study plans to evaluate the extent to which the factors that enable IoMT application diffusion influence the adoption behaviour of healthcare professionals, I am sending this questionnaire to you with a request to complete it. I will therefore be very grateful to you if you would participate in the survey to enable me to complete this important research. Participation in this research is entirely voluntary. Hence, I request you to spare a few moments of your valuable time to participate in this study. If you decide to take part, you will be given this information sheet to keep and be asked to sign a consent form. Even after deciding to take part in the research, you are still free to withdraw at any time and without giving any reason. I assure you that the information provided by you, will only be used for the purpose of this research, and will be treated in the strictest confidence possible, and your identity will be kept anonymous. I also guarantee you that all the information provided by you will not be allowed to be used by any third party or entity. The study has obtained ethical approval from Bradford University, UK.

If you require any clarification, please do not hesitate to contact me on the telephone and/ or e-mail details provided below. Thanking you for your kind cooperation and support for this important study.

Yours sincerely,

Fatema Al Dhaen

Appendix 8

Research Instrument

Section I: Demographic

Your gender:

○ Female ○ Male ○ Prefer not to say

Your age (in Years):

○ 18-25 ○ 26-33 ○ 34-41 ○ 42-49 ○ Over 50

Please provide information about your professional status by ticking in the box against the most appropriate of the ones given below

Hospital doctors	
Community Health Services doctors	
Consultant doctors	
General practitioners	
Allied healthcare professional	
Pharmacist	
Healthcare scientist + (e.g., cervical cytology screener, phlebotomist, newborn hearing screener and healthcare science assistant/associate) (retained: explanation provided)	
Nurses and Health Visitors	
Ambulance staff	
Other GP Practice staff (direct patient care) +++ (e.g., other staff involved in providing direct patient care, which includes clinical pharmacists, dispensers, phelbotomists, therapists, healthcare assistants and others).	
Other GP Practice staff (admin) ++++ (e.g., Receptionist and administrative staff)	

Please indicate the level of your education qualification:

◯ High school graduate or equivalent ◯ Bachelor's degree ◯ Master's degree ◯ Professional certificate ◯ Doctorate

Please choose the most appropriate one of the following that applies to you:

◯ Using IoMT currently ◯ Aware of IoMT ◯ Intend to use IoMT in future ◯ Not familiar with IoMT

<u>Section II</u>

This section is about your continuous intention to use IoMT in your day-to-day professional job.

Please rate with an "X" each item on the five-point Likert scale shown, to indicate your level of agreement with the statement.

1-Strongly Disagree, 2- Disagree, 3-Neutral, 4-Agree, 5-Strongly Agree

Please note: Internet of medical things (IoMT) (e.g., wearables, smart continuous glucose monitoring, insulin pens, smart watches for depression, heart rate monitoring and remote patient monitoring) are technologically enabled medical innovation that could result in new business models, applications, processes or products with an associated material effect on patientcare and provision of healthcare services.

Item	1	2	3	4	5
Given the chance, I intend to use IoMT applications.					
I am willing to use IoMT applications in the near future.					
I will recommend IoMT applications to others.					
I will continue using IoMT applications in the future.					
Using an IoMT application enables me to complete tasks faster.					
Using an IoMT application improves the quality of work I do.					
Using an IoMT application makes it easier to do my job.					
Using an IoMT enhances my effectiveness on the job.					
Using an IoMT gives me greater control over my work.					
Using an IoMT increases my productivity.					
The use of IoMT requires a lot of mental effort. CPX1 ** (retained)					
The use of IoMT is frustrating. CPX2 ** (retained)					

The use of IoMT is too complex for business operations.					
The skills needed to adopt IoMT are too complex for employees of the firm.					
Using an IoMT is compatible with all aspects of my work.					
Using an IoMT is completely compatible with my current situation.					
I think that using an IoMT fits well with the way I like to work.					
The use of IoMT is fully compatible with the value system of my workplace.					
I have had a great opportunity to try different IoMT applications.					
I am aware where I can go to try out many uses of IoMT.					
Before deciding on whether to use IoMT applications, I was in a position to properly try them out.					
I was permitted to use IoMT applications on a trial basis over a long and sufficient period of time to see what it can do.					
I have seen what others do while using IoMT.					
In my organisation, one sees IoMT applications used in different units.					
I have seen the use of IoMT outside my organisation.					
I have had many opportunities to see IoMT being used.					
My performance was satisfactory on the IoMT application training.					
I was able to achieve the objectives of IoMT application training.					
I could learn as much as possible from the training on IoMT.					
I was able to benefit from the training on IoMT.					
The training on IoMT significantly added to my knowledge.					
I receive enough information about AI in from service provider of IoMT. [AI is a branch of science that helps machines find the right solution for solving complex problems in a human-like way. Example: Telemedicine, Voice assistants in the clinic, Apple's Siri, Amazon's Alexa, Google's Google Home, Samsung's Bixby and Microsoft's Cortana].					
I receive enough information about the benefits of AI integrated in IoMT.					
I receive enough information of using AI integrated in IoMT.					
I am aware of the education/training programs about using AI integrated in IoMT offered by the service provider.					
I am aware of the importance of ethics (e.g., ensuring security and privacy of user data) while using AI integrated in IoMT.					

I have come across campaigns by the service provider about using AI integrated in IoMT.					
While using IoMT, I am always seeking new ideas about IoMT.					
While using IoMT, I am always seeking new experience about IoMT.					
I do not prefer an unpredictable way while using IoMT but prefer the one without any change in my routine use of IoMT.					
I like to continually change my way of dealing with IoMT activities.					
I do not like meeting IoMT service providers who have new ideas about IoMT.					
I like to experience novelty in IoMT.					
My job requires me to use it.					
I think it is interesting.					
I feel good when using it.					
I think that this activity is good for me.					
I believe that this activity is important for me.					

Thank you for taking out your time to complete the survey.

Appendix 9

Descriptive Statistics

Item code	Items	N Valid	N Missing	Mean	Std. Deviation	Min.	Max.
	Gender	38.00	0.00	1.71	0.46	1.00	2.00
	Age	38.00	0.00	2.79	1.21	1.00	5.00
	Professional Status	0.00	38.00				
	Educational Qualification	38.00	0.00	2.87	1.12	2.00	5.00
	Usage of IoMT	38.00	0.00	2.58	1.37	1.00	4.00
CI1	Given the chance, I intend to use IoMT applications.	38.00	0.00	3.84	1.28	1.00	5.00
CI2	I am willing to use IoMT applications in the near future.	38.00	0.00	4.11	1.20	1.00	5.00
CI3	I will recommend IoMT applications to others.	38.00	0.00	3.84	1.20	1.00	5.00
CI4	I will continue using IoMT applications in the future.	38.00	0.00	3.97	1.24	1.00	5.00
RA1	Using an IoMT application enables me to complete tasks faster.	38.00	0.00	3.68	1.36	1.00	5.00
RA2	Using an IoMT application improves the quality of work I do.	38.00	0.00	3.87	1.28	1.00	5.00
RA3	Using an IoMT application makes it easier to do my job.	38.00	0.00	3.84	1.31	1.00	5.00
RA4	Using an IoMT enhances my effectiveness on the job.	38.00	0.00	3.87	1.21	1.00	5.00
RA5	Using an IoMT gives me greater control over my work.	38.00	0.00	3.79	1.23	1.00	5.00
RA6	Using an IoMT increases my productivity.	38.00	0.00	3.97	1.22	1.00	5.00
CPX1	The use of IoMT requires a lot of mental effort.	38.00	0.00	3.42	1.31	1.00	5.00
CPX2	The use of IoMT is frustrating.	38.00	0.00	2.87	1.09	1.00	5.00
CPX3	The use of IoMT is too complex for business operations.	38.00	0.00	2.71	1.11	1.00	5.00
CPX4	The skills needed to adopt IoMT are too complex for employees of the firm.	38.00	0.00	2.74	1.16	1.00	5.00
CMP1	Using an IoMT is compatible with all aspects of my work.	38.00	0.00	3.26	1.11	1.00	5.00
CMP2	Using an IoMT is completely compatible with my current situation.	38.00	0.00	3.53	1.18	1.00	5.00
CMP3	I think that using an IoMT fits well with the way I like to work.	38.00	0.00	3.79	1.23	1.00	5.00
CMP4	The use of IoMT is fully compatible with the value system of my workplace.	38.00	0.00	3.61	1.24	1.00	5.00
TRI1	I have had a great opportunity to try different IoMT applications.	36.00	2.00	3.31	1.45	1.00	5.00
TRI2	I am aware of where I can go to try out many uses of IoMT.	38.00	0.00	3.03	1.17	1.00	5.00
TRI3	Before deciding on whether to use IoMT applications, I was in a position to properly try them out.	38.00	0.00	3.13	1.30	1.00	5.00
TRI4	I was permitted to use IoMT applications on a trial basis over a long and sufficient period of time to see what it can do.	38.00	0.00	2.84	1.15	1.00	5.00
OBS1	I have seen what others do while using IoMT.	38.00	0.00	3.13	1.23	1.00	5.00
OBS2	In my organisation, one sees IoMT applications used in different units.	38.00	0.00	3.05	1.45	1.00	5.00
OBS3	I have seen the use of IoMT outside my organisation.	38.00	0.00	2.74	1.33	1.00	5.00
OBS4	I have had many opportunities to see IoMT being used.	38.00	0.00	2.89	1.11	1.00	5.00
TRN1	My performance was satisfactory on the IoMT application training.	38.00	0.00	3.00	0.99	1.00	5.00

TRN2	I was able to achieve the objectives of IoMT application training.	38.00	0.00	3.21	0.99	1.00	5.00
TRN3	I could learn as much as possible from the training on IoMT.	38.00	0.00	3.50	1.11	1.00	5.00
TRN4	I was able to benefit from the training on IoMT.	38.00	0.00	3.47	1.06	1.00	5.00
TRN5	The training on IoMT significantly added to my knowledge.	38.00	0.00	3.53	1.01	1.00	5.00
AWS1	I receive enough information about AI in from service provider of IoMT.	38.00	0.00	3.05	1.37	1.00	5.00
AWS2	I receive enough information about the benefits of AI integrated in IoMT.	38.00	0.00	2.84	1.17	1.00	5.00
AWS3	I receive enough information of using AI integrated in IoMT.	38.00	0.00	2.95	1.29	1.00	5.00
AWS4	I am aware of the education/training programs about using AI integrated in IoMT offered by the service provider.	38.00	0.00	2.95	1.31	1.00	5.00
AWS6	I am aware of the importance of ethics (e.g., ensuring security and privacy of user data) while using AI integrated in IoMT.	38.00	0.00	3.68	1.23	1.00	5.00
AWS5	I have come across campaigns by the service provider about using AI integrated in IoMT.	38.00	0.00	2.71	1.16	1.00	5.00
NS1	While using IoMT, I am always seeking new ideas about IoMT.	38.00	0.00	3.24	1.02	1.00	5.00
NS2	While using IoMT, I am always seeking new experience about IoMT.	38.00	0.00	3.42	1.20	1.00	5.00
NS3	I do not prefer an unpredictable way while using IoMT but prefer the one without any change in my routine use of IoMT.	38.00	0.00	3.37	1.08	1.00	5.00
NS4	I like to continually change my way of dealing with IoMT activities.	38.00	0.00	3.29	0.98	1.00	5.00
NS5	I do not like meeting IoMT service providers who have new ideas about IoMT.	38.00	0.00	2.79	0.87	1.00	5.00
NS6	I like to experience novelty in IoMT.	38.00	0.00	3.39	1.08	1.00	5.00
MOT2	I think it is interesting.	38.00	0.00	3.32	1.21	1.00	5.00
MOT1	My job requires me to use it.	38.00	0.00	3.82	1.18	2.00	5.00
MOT3	I feel good when using it.	38.00	0.00	3.47	1.13	1.00	5.00
MOT4	I think that this activity is good for me.	38.00	0.00	3.84	1.08	2.00	5.00
MOT5	I believe that this activity is important for me.	38.00	0.00	4.11	1.09	2.00	5.00

Appendix 10

Structural Equation Modelling terminology

No.	Term	Interpretation	Author /s
1.	Observed variable (Manifest variable)	Variables that are measured effectively like using a Likert scale. These are referred to as items or questions. They are also referred to as indicators.	Janssens et al. (2008); Abramson et al. (2005)
2.	Non-observed variable (latent variable)	These variables are not measured directly. These variables are measured or estimated based on the score for and the variance of the observed variable.	Janssens et al. (2008)
		Latent variables are those which are theoretical constructions of manifest variables. Latent variables equate to factors in factor analysis.	Abramson et al. (2005); Arbuckle and Wothke (1999); Byrne, (2001); Joreskog (1977, 1993); Kline (1998); Ullman (2001)
3.	Endogenous variables	Variables that are of interest and are explained within the constraints of the model being tested.	Byrne (2001); Kline (1998)
		These variables equate with dependent variables in multiple regression analysis.	Byrne (2001); Joreskog (1993)
4.	Exogenous variables	Variables used to explain relationships within the model.	Byrne (2001); Kline (1998)
		These variables equate with independent variables in multiple regression analysis.	Byrne (2001); Joreskog (1993)
5.	Non-recursive models	Models that have bidirectional "causal" relationships, that is, feedback loops, correlated error terms, or both.	Arbuckle and Wothke (1999); Byrne (2001); Kline (1998); Ullman (2001)
6.	Recursive models	Variables that have unidirectional "causal" relationships and independent error terms.	Arbuckle and Wothke (1999); Byrne (2001); Kline (1998); Ullman (2001)
7.	Moderators	Variables that interact with the relationship of one variable's impact on another's.	Baron and Kenny (1986)
8.	Mediators	Variables that affect the relationship between two other variables. Mediators come between two variables such that the first variable has an indirect effect on the second variable, through its direct effect on the mediator.	Baron and Kenny (1986)
9.	Error term	Non-observable; determine the unique variance of a variable.	Janssens et al. (2008)
10.	Double pointed arrows	Indicate correlations and covariances.	Janssens et al. (2008)
11.	Single pointed arrows	Indicate causal effects	Janssens et al. (2008)

Appendix 11

Sample correlation

	CI4	CI3	CI2	CI1	OBS1	OBS2	OBS4	TRN1	TRN5	TRN4	TRN3	TRN2	MOT 1	MOT 5	MOT 4	MOT 3	TRI1	TRI2	CMP 2	CMP 3	CMP 4	RA6	RA5	RA1	RA2	RA3	RA4	CPX3	CPX4
CI4	1.00																												
CI3	0.75	1.00																											
CI2	0.82	0.75	1.00																										
CI1	0.70	0.66	0.76	1.00																									
OBS1	0.18	0.19	0.21	0.18	1.00																								
OBS2	0.24	0.21	0.23	0.15	0.53	1.00																							
OBS4	0.31	0.26	0.26	0.24	0.51	0.51	1.00																						
TRN1	0.32	0.25	0.30	0.27	0.54	0.54	0.63	1.00																					
TRN5	0.40	0.34	0.42	0.32	0.46	0.45	0.56	0.73	1.00																				
TRN4	0.37	0.31	0.39	0.30	0.47	0.41	0.57	0.69	0.81	1.00																			
TRN3	0.40	0.26	0.41	0.29	0.46	0.38	0.50	0.65	0.80	0.80	1.00																		
TRN2	0.37	0.30	0.34	0.26	0.55	0.45	0.60	0.80	0.76	0.78	0.74	1.00																	
MOT 1	0.44	0.40	0.45	0.41	0.34	0.27	0.34	0.42	0.40	0.36	0.34	0.41	1.00																
MOT 5	0.51	0.42	0.48	0.40	0.28	0.22	0.34	0.40	0.47	0.42	0.46	0.39	0.64	1.00															
MOT 4	0.53	0.44	0.49	0.43	0.30	0.25	0.33	0.44	0.50	0.43	0.48	0.44	0.71	0.83	1.00														
MOT 3	0.53	0.39	0.46	0.41	0.33	0.29	0.40	0.49	0.52	0.48	0.50	0.51	0.73	0.73	0.85	1.00													
TRI1	0.28	0.23	0.24	0.26	0.55	0.38	0.48	0.50	0.46	0.47	0.45	0.52	0.33	0.38	0.38	0.39	1.00												
TRI2	0.31	0.27	0.31	0.29	0.50	0.33	0.47	0.39	0.40	0.41	0.38	0.46	0.35	0.32	0.38	0.42	0.70	1.00											
CMP 2	0.50	0.50	0.45	0.38	0.23	0.22	0.32	0.33	0.36	0.38	0.28	0.39	0.47	0.48	0.47	0.49	0.36	0.35	1.00										
CMP 3	0.51	0.48	0.47	0.38	0.27	0.31	0.30	0.39	0.45	0.40	0.36	0.40	0.52	0.63	0.58	0.59	0.30	0.34	0.65	1.00									
CMP 4	0.42	0.38	0.44	0.35	0.31	0.24	0.25	0.33	0.36	0.29	0.34	0.36	0.48	0.46	0.43	0.46	0.43	0.43	0.62	0.58	1.00								
RA6	0.61	0.50	0.60	0.48	0.23	0.21	0.27	0.38	0.36	0.36	0.42	0.40	0.45	0.58	0.60	0.57	0.30	0.32	0.47	0.53	0.40	1.00							
RA5	0.64	0.56	0.57	0.49	0.25	0.23	0.26	0.31	0.36	0.29	0.36	0.34	0.48	0.55	0.53	0.52	0.30	0.29	0.49	0.52	0.44	0.77	1.00						
RA1	0.72	0.61	0.67	0.56	0.21	0.23	0.32	0.33	0.38	0.38	0.38	0.35	0.49	0.55	0.53	0.52	0.29	0.29	0.47	0.51	0.45	0.63	0.71	1.00					
RA2	0.68	0.62	0.65	0.54	0.23	0.20	0.29	0.33	0.42	0.37	0.39	0.37	0.44	0.58	0.55	0.54	0.31	0.30	0.46	0.59	0.39	0.75	0.77	0.79	1.00				
RA3	0.65	0.57	0.59	0.51	0.29	0.23	0.29	0.37	0.38	0.35	0.39	0.41	0.50	0.53	0.52	0.54	0.33	0.31	0.47	0.53	0.46	0.73	0.79	0.77	0.80	1.00			
RA4	0.68	0.59	0.66	0.53	0.21	0.22	0.23	0.32	0.41	0.34	0.37	0.33	0.43	0.57	0.52	0.51	0.30	0.30	0.48	0.58	0.42	0.80	0.81	0.74	0.84	0.79	1.00		
CPX3	0.01	-0.06	-0.03	-0.07	0.09	0.16	0.09	0.17	0.22	0.16	0.23	0.14	-0.10	-0.05	0.00	-0.01	0.07	0.10	-0.05	-0.06	-0.03	0.00	-0.03	-0.07	-0.03	-0.07	0.04	1.00	
CPX4	-0.04	-0.05	-0.05	-0.13	0.12	0.10	0.06	0.20	0.18	0.11	0.22	0.17	-0.06	0.03	0.05	0.01	0.08	0.09	0.00	0.00	0.04	0.06	-0.04	-0.08	0.02	-0.04	0.04	0.69	1.00

Appendix 12

Confirmatory factor analysis of the model with moderators

Sample Correlations (Group number 1)

	NS2	NS1	AWS3	AWS2	CI4	CI3	CI2	CI1	OBS1	OBS2	OBS3	OBS4	TRN1	TRN5	TRN3	TRN2	MOT1	MOT4	MOT3	TRI1	TRI2	TRI4	CMP2	CMP3	RA6	RA5	RA2	RA3	RA4	CPX2	CPX3
NS2	1.00																														
NS1	0.88	1.00																													
AWS3	0.48	0.49	1.00																												
AWS2	0.51	0.52	0.90	1.00																											
CI4	0.40	0.42	0.30	0.24	1.00																										
CI3	0.37	0.36	0.31	0.25	0.75	1.00																									
CI2	0.36	0.38	0.30	0.25	0.82	0.75	1.00																								
CI1	0.31	0.32	0.25	0.20	0.70	0.66	0.76	1.00																							
OBS1	0.37	0.38	0.44	0.43	0.18	0.19	0.21	0.18	1.00																						
OBS2	0.33	0.30	0.39	0.36	0.24	0.21	0.23	0.15	0.53	1.00																					
OBS3	0.43	0.35	0.51	0.50	0.26	0.26	0.25	0.22	0.51	0.43	1.00																				
OBS4	0.41	0.42	0.51	0.48	0.31	0.26	0.26	0.24	0.51	0.51	0.58	1.00																			
TRN1	0.45	0.45	0.60	0.58	0.32	0.25	0.30	0.27	0.54	0.54	0.49	0.63	1.00																		
TRN5	0.51	0.51	0.62	0.59	0.40	0.34	0.42	0.32	0.46	0.45	0.44	0.56	0.73	1.00																	
TRN3	0.51	0.49	0.56	0.56	0.40	0.26	0.41	0.29	0.46	0.38	0.44	0.50	0.65	0.80	1.00																
TRN2	0.50	0.52	0.64	0.60	0.37	0.30	0.34	0.26	0.55	0.45	0.48	0.60	0.80	0.76	0.74	1.00															
MOT1	0.44	0.45	0.44	0.43	0.44	0.40	0.45	0.41	0.34	0.27	0.37	0.34	0.42	0.40	0.34	0.41	1.00														
MOT4	0.55	0.52	0.46	0.47	0.53	0.44	0.49	0.43	0.30	0.25	0.40	0.33	0.44	0.50	0.48	0.44	0.71	1.00													
MOT3	0.56	0.54	0.50	0.50	0.53	0.39	0.46	0.41	0.33	0.29	0.41	0.40	0.49	0.52	0.50	0.51	0.73	0.85	1.00												
TRI1	0.35	0.36	0.40	0.37	0.28	0.23	0.24	0.26	0.55	0.38	0.38	0.48	0.50	0.46	0.45	0.52	0.33	0.38	0.39	1.00											
TRI2	0.39	0.42	0.43	0.40	0.31	0.27	0.31	0.29	0.50	0.33	0.38	0.47	0.39	0.40	0.38	0.46	0.35	0.38	0.42	0.70	1.00										
TRI4	0.42	0.43	0.44	0.45	0.22	0.17	0.22	0.13	0.47	0.36	0.32	0.42	0.48	0.47	0.50	0.57	0.21	0.33	0.35	0.58	0.57	1.00									
CMP2	0.31	0.31	0.35	0.30	0.50	0.50	0.45	0.38	0.23	0.22	0.31	0.32	0.33	0.36	0.28	0.39	0.47	0.47	0.49	0.36	0.35	0.23	1.00								
CMP3	0.38	0.35	0.40	0.35	0.51	0.48	0.47	0.38	0.27	0.31	0.36	0.30	0.39	0.45	0.36	0.40	0.52	0.58	0.59	0.30	0.34	0.24	0.65	1.00							
RA6	0.40	0.41	0.33	0.36	0.61	0.50	0.60	0.48	0.23	0.21	0.22	0.27	0.38	0.36	0.42	0.40	0.45	0.60	0.57	0.30	0.32	0.35	0.47	0.53	1.00						
RA5	0.41	0.45	0.27	0.28	0.64	0.56	0.57	0.49	0.25	0.23	0.24	0.26	0.31	0.36	0.36	0.34	0.48	0.53	0.52	0.30	0.29	0.29	0.49	0.52	0.77	1.00					
RA2	0.40	0.41	0.32	0.29	0.68	0.62	0.65	0.54	0.23	0.20	0.22	0.29	0.33	0.42	0.39	0.37	0.44	0.55	0.54	0.31	0.30	0.34	0.46	0.59	0.75	0.77	1.00				
RA3	0.39	0.42	0.32	0.33	0.65	0.57	0.59	0.51	0.29	0.23	0.25	0.29	0.37	0.38	0.39	0.41	0.50	0.52	0.54	0.33	0.31	0.34	0.47	0.53	0.73	0.79	0.80	1.00			
RA4	0.35	0.34	0.29	0.27	0.68	0.59	0.66	0.53	0.21	0.22	0.19	0.23	0.32	0.41	0.37	0.33	0.43	0.52	0.51	0.30	0.30	0.30	0.48	0.58	0.80	0.81	0.84	0.79	1.00		
CPX2	0.05	0.04	0.11	0.15	-0.11	-0.07	-0.05	-0.11	0.13	0.02	0.17	0.05	0.11	0.10	0.15	0.09	-0.10	-0.02	-0.07	0.05	0.04	0.17	-0.04	-0.07	0.01	-0.04	-0.12	-0.12	-0.04	1.00	
CPX3	0.10	0.09	0.12	0.12	0.01	-0.06	-0.03	-0.07	0.09	0.16	0.13	0.09	0.17	0.22	0.23	0.14	-0.10	0.00	-0.01	0.07	0.10	0.24	-0.05	-0.06	0.00	-0.03	-0.03	-0.07	0.04	0.62	1.00

Appendix 12 (continued)

Confirmatory factor analysis of the model with moderators

Squared Multiple Correlations: (Group number 1 - Default model

			Estimate
NS2			0.875
NS1			0.886
AWS3			0.921
AWS2			0.884
CI4			0.82
CI3			0.689
CI2			0.829
CI1			0.634
OBS1			0.529
OBS2			0.422
OBS3			0.483
OBS4			0.607
TRN1			0.729
TRN5			0.768
TRN3			0.695
TRN2			0.805
MOT1			0.614
MOT4			0.829
MOT3			0.867
TRI1			0.702
TRI2			0.662
TRI4			0.512
CMP2			0.572
CMP3			0.749
RA6			0.727
RA5			0.765
RA2			0.815
RA3			0.761
RA4			0.848
CPX2			0.485
CPX3			0.786

Appendix 12 (continued)

Confirmatory factor analysis of the model with moderators

Goodness fit of the model (covariance model with moderators)

Model	NPAR	CMIN	DF	P	CMIN/DF
Default model	107	954.056	389	0	2.453
Saturated model	496	0	0		
Independence model	31	9621.734	465	0	20.692
RMR, GFI					
Model	RMR	GFI	AGFI	PGFI	
Default model	0.047	0.85	0.809	0.667	
Saturated model	0	1			
Independence model	0.514	0.157	0.101	0.147	

RMSEA				
Model	RMSEA	LO 90	HI 90	PCLOSE
Default model	0.064	0.059	0.069	0
Independence model	0.236	0.232	0.24	0