



Advancing the Understanding of the Role of Responsible AI in the Continued Use of IoMT in Healthcare

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Abstract

This paper examines the continuous intention by healthcare professionals to use the Internet of Medical Things (IoMT) in combination with responsible artificial intelligence (AI). Using the theory of Diffusion of Innovation (DOI), a model was developed to determine the continuous intention to use IoMT taking into account the risks and complexity involved in using AI. Data was gathered from 276 healthcare professionals through a survey questionnaire across hospitals in Bahrain. Empirical outcomes reveal nine significant relationships amongst the constructs. The findings show that despite contradictions associated with AI, continuous intention to use behaviour can be predicted during the diffusion of IoMT. This study advances the understanding of the role of responsible AI in the continued use of IoMT in healthcare and extends DOI to address the diffusion of two innovations concurrently.

Keywords Internet of medical things · Diffusion of innovation · Artificial intelligence · Awareness · Novelty seeking · Responsible AI

1 Introduction

The Internet of medical things (IoMT) and its advancements (Ghubaish et al., 2021; Giri et al., 2019) are attracted by numerous advantages. Responsible AI when integrated with IoMT offers the world of healthcare and the medical profession multiple benefits which encourage the profession to leave behind existing technologies in favour of IoMT. However, when two new innovations, which are still diffusing and are

not yet fully institutionalised are introduced to a new setting and users are expected to adopt those, concerns arise in the minds of users in regard to the advantage vis-à-vis other similar or equivalent technologies (Ryu, 2018; Choi et al., 2020; de Oca Munguia et al., 2021). Furthermore, in the case of IoMT embedded with AI, which is akin to a new technology embedded in an innovation, more concerns could arise in the minds of users on the extent to which IoMT could be a useful technology aided by AI. The problem becomes complicated when IoMT is still seen to be diffusing (Coventry & Branley, 2018; Lee & Yoon, 2021; Safavi & Kalis, 2019).

The integration of AI into IoMT, while promising to offer many benefits including self-decision making and attempts to replace a human being presents the user and/or organisation with serious risks and an ethical dilemma. This is the case if the decisions made by AI are not accountable and trustworthy (Scott & Yampolskiy, 2019). A study by Reardon (2019) shows that claims of AI performing better than radiologists were not supported by solid evidence. Here, the concept of responsible AI assumes importance which could include ethical, social and participation concerns including pervasive human/machine interactions that could lead to risks (Dignum, 2017). For instance, challenges related to ethics, social aspects and participation of users while adopting IoMT can lead to a situation wherein it is difficult to control the technology (e.g., information and communication

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technology) on which IoMT is built (Dignum, 2017; Shah & Chircu, 2018). These aspects could impact healthcare professionals. One aspect of the diffusion of AI based IoMT is that it can impact the continuous intention to use IoMT of healthcare professionals and usage of IoMT (Miraz et al., 2018). Literature shows that while studies concerning behavioural intention to use IoMT continuously have been found, a study of the linkage of the factors or barriers that affect continuous intention to use (the process by which IoMT is accepted and used) IoMT by users is lacking (Lu et al., 2018). Investigation into factors affecting continuous intention to use IoMT could lead to predictability of the continuous intention to use IoMT with responsible AI. Lack of knowledge on the predictability of continuous intention to use behaviour of users of IoMT with responsible AI can have a devastating effect on the healthcare professionals, patients, hospitals, innovators, suppliers, and manufacturers, which is a key gap in the literature.

While arguing that there could be a linkage between the diffusion factors (predictor) and continuous intention to use IoMT (predicted), this research posits that between the predictor and predicted, there could also be other factors related to behavioural aspects of users that could play a role as argued by DOI (Rogers, 2003). Thus, a research question that needs to be answered is what factors predict the continuous intention to use IoMT directly and indirectly while IoMT is still diffusing? The aim of this research was to investigate the continuous intention to use IoMT by healthcare professionals characterized by responsible AI and factors that affect it. In order to answer this question, the research was conducted in the healthcare sector in Bahrain, a developing economy in the Gulf Cooperation Council (GCC), by studying healthcare professionals who have used or were using IoMT in the work setting. A survey was used to collect data from a representative sample of 276 healthcare professionals in August 2020.

At this point, two assumptions have been made at the core of this research. One is that although IoMT is still an evolving technology, it is possible to investigate the evolution through the prism of diffusion. The second is that factors that encourage the continuous intention to use IoMT are likely to be stronger than those that impede the continuous intention to use it, thus bringing into focus user behaviour towards the usage of IoMT embedded with responsible AI. While the natural instincts of users are more likely to drive them to upgrade existing technology to later versions, hence impeding their continuous intention to use current versions, in the case of IoMT there appears to be compelling factors that could encourage users to continuously use particular versions of the technology. These two assumptions form the basis of this research.

The rest of the paper is organized as follows: The relevant literature reviewed is presented in Section 2 followed by the conceptual model and hypotheses development in Section 3. Section 4 presents the research methodology whereas data

analysis in Section 5. Section 6 presents the discussion. Finally, Section 7 presents the conclusion along with limitations and future research directions.

2 Literature Review

A review of the extant literature is presented in this section about the factors and barriers affecting the continuous intention to use IoMT. Continuous intention to use as a construct signifies an important aspect of user behaviour and indicates the post-acceptance behaviour of a technology (Zhanyou et al., 2020).

2.1 Factors Affecting the Continuous Intention to Use IoMT

According to the literature, the successful and sustained use (continuous intention to use) (Kim et al., 2019) of IoMT is affected by certain factors that are still not well researched (Matheny et al., 2019). Regarding continuous intention to use IoMT, medical professionals are giving mixed signals on its acceptance and continuous use. Some state it is worth using IoMT or any smart device because of the relative advantage it offers in comparison to the existing techniques while others say that it is a complex technology and difficult to use (Mavrogiorgou et al., 2019; Zeadally et al., 2019). The literature shows that IoMT is still evolving, and its use is in its infancy (Kamilaris & Botteghi, 2020). This indicates that the diffusion of IoMT could be associated with IoMT usage. These examples suggest that a detailed review of the literature could uncover more factors that influence continuous intention to use IoMT. Subsequent examination of the various studies in the literature showed that user intention to continuously use IoMT is a major concern for innovators, manufacturers, suppliers, researchers and technologists (Taylor et al., 2018). While literature shows that there is no certainty on the list of factors or number of factors that affect the continuous intention to use IoMT, the outcome of some studies is showing encouraging results in this regard. For instance, user attitudes, motivations and behaviours (Abildgaard et al., 2016), training (Saarikko et al., 2017), the relative advantage of IoMT, the complexity of IoMT, compatibility of IoMT, trialability of IoMT, observability of IoMT (Al-Rahmi et al., 2019), awareness about AI (Mansour et al., 2019), age (Venkatesh et al., 2012) and novelty-seeking behaviour (Tsao & Yang, 2017) were found to be some of the factors identified in the literature as affecting continuous intention to use IoMT embedded with responsible AI. However, research in these studies do not address the issue of IoMT embedded with responsible AI when both are diffusing concurrently and the interaction amongst those factors in one holistic model. This research addresses this issue.

2.2 Barriers Affecting the Continuous Intention to Use IoMT

Research has found that several barriers affect the continuous use of IoMT by healthcare professionals in supporting patients and such barriers need to be removed if IoMT usage has to be improved. Literature shows that barriers to the usage of IoT and therefore IoMT, include illiteracy on the part of the user related to technology, failure of technology due to its poor management, and the high level of training needed (Nijeweme-d'Hollosy et al., 2015). Other barriers include lack of awareness, lack of value perception of customers, behavioural challenges, cost, security, handling new technology, lack of qualified workforce and employee resistance (Ericsson, 2015; Padyab et al., 2019; Winchcomb et al., 2017). Despite such barriers, if users continue to use IoMT then the use of IoMT by both patients and patient-care providers could not be considered as an automatic occurrence. In fact, literature shows that a study of the linkage of the factors or barriers that affect continuous intention to use (the process by which IoMT is accepted and used) IoMT to continuous intention to use IoMT by users is lacking (Lu et al., 2018).

In order to address the above issues and 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 of this research. They are conceived as the determinants of the behavioural intention of the use of IoMT-with responsible AI - by healthcare professionals. In addition to this, some researchers (Baudier et al., 2019; Lee et al., 2005; Van der Heijden, 2004; Venkatesh et al., 2002) have argued that motivation is an important aspect in the usage of technology, continuous intention to use technology or behavioural intention to use technology, an argument which could be extended to IoMT usage. It is argued further that better understanding of the motivation of people concerned with usage or behavioural intention to use technology including IoT and IoMT could be useful in improving the usage or behavioural intention to use IoMT, knowledge about which is not clear in the literature (Baudier et al., 2019). This is an important gap in the literature which if addressed is expected to bring out new knowledge on how to motivate users to use IoMT and enhance the usage of IoMT-with responsible AI to the betterment of patient care. Similarly, another factor that was considered essential to this research was training in IoMT. It was argued in the literature (Ozkeser, 2019) that training is nearly an inseparable part of IoMT and an associate factor of the motivation of users. Innovations in IoMT involve complex technologies and understanding on how to use them over a long term requires the support of technicians who can help healthcare professionals to develop the needed skills to use IoMT devices through training. However, literature shows that there is a lack of knowledge and research outcomes on

how training in IoMT as a concept has to be understood with regard to the use of technologies and new technologies (Al-Gahtani, 2016; Gaynor et al., 2015) especially so with regard to a currently diffusing technology. To what extent motivation and its associated concept of training in IoMT affect acceptance of IoMT and its use after acceptance, when it is still diffusing, is not well understood in the literature as hardly any research publication addressing this aspect can be found in the literature.

2.3 Effect of Responsible AI on IoMT

IoMT is a fairly new concept and is considered a novel idea (Rodrigues et al., 2018) and is combined with responsible AI that is constantly reshaping services (Huang & Rust, 2018). Literature (Sugandini et al., 2018) shows that the perceived behaviour of users of new or novel products is significantly affected by the new product trial. IoMT associated with responsible AI being a new and novel concept, this factor is also considered as important for this research as a moderator of the relationship between antecedents of continuous intention to use IoMT, and continuous intention to use IoMT. If one argues that technology is a phenomenon that affects any field including IoMT, it is inevitable that awareness about the impact of those technologies on the users becomes a major concern. This is due to the tendency of technological innovations being more complex and a lack of awareness about using those technologies could pose a challenge (Chen et al., 2020). This is echoed by Gómez-González et al. (2020) who argue that AI and AI-mediated technologies in medicine and healthcare need to be studied concerning principles, ethical and societal guidelines, and potential boundaries, as these areas are challenging and responses to those challenges are not yet well developed.

3 Theoretical Background, Conceptual Model and Hypotheses Development

3.1 Theoretical Background

Common examples of theories that have been used by researchers to predict acceptance and usage of new technological innovations found in the literature include the theory of reasoned action (TRA) (Buabeng-Andoh et al., 2019), the theory of planned behaviour (TPB) (Li et al., 2020), technology acceptance model (TAM) (Deng et al., 2018), DOI (Mohammadi et al., 2018), task technology fit (TTF) (Shahbaz et al., 2019) and unified theory of acceptance and use of technology (UTAUT) (Alam et al., 2018). Continuous use of IoMT or behavioural intention of users of IoMT-with responsible AI is not easy to predict because of the involvement of many different factors that affect users although DOI

has been shown to have the ability to clarify behavioural aspects of users in relation to innovation and its diffusion, according to a crucial study by Rogers (2003).

DOI talks about innovation and how it diffuses across the users and brings into focus the need to understand the adopter and the adopted (Rogers, 2003). But it talks about only a single innovation that diffuses at a single point of time and is accepted once. While literature shows that the phenomenon of diffusion of innovation cannot be substituted with other theories. At the same time diffusion cannot also explain all the reasons why people adopt an innovation or how the innovation diffuses (Taherdoost, 2018). In contrast, the speed with which an innovation penetrates a market and is adopted could not be explained by such theories as TRA, TPB, TAM and UTAUT (Fry et al., 2018). One of the reasons for this is that these four theories focused on the adopter and the people surrounding the adopter which is linked to their perception and intentions. In addition, the base for TPB and TAM is the TRA while UTAUT is a more complex model that depends on eight different models. It was therefore concluded that the nearest theory that can be seen to support this study is the DOI and hence this theory has been used as the base for this research. Despite its limitation on how certain repetitions of an innovation diffuse or fail to diffuse, it was thought worthwhile to apply this theory to understand how an innovation like IoMT or its subsequent manifestation will be accepted and continuously used by healthcare professionals.

It is important to understand whether an innovation like IoMT is likely to be accepted and used by the users' mid-stream through the different stages of the diffusion of the innovation or after the innovation has fully diffused and resulted into continuous use. 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 eventually predict its acceptance and continued use.

3.2 Proposed Conceptual Model

The focus of the present study is on how to predict the continuous intention to use IoMT. From the literature review, three sets of factors have been identified as affecting the continuous intention to use IoMT. The first set of factors are diffusion factors. Literature shows that the perception of relative advantage, compatibility, complexity, observability and trialability of the technology of the users can influence the continuous intention to use technology (Rogers, 2003).

The second set of factors include intervention factors. Motivation is expected to be generated by the ease of use and usefulness of IoMT. Similarly, a lack of training could be a threat to the users of IoMT (Saarikko et al., 2017) and hence identified as a driver of continuous use of IoMT during the process of diffusion. Here it must be mentioned that usage

implies continuous intention to use following the first use of technology and maintain such usage of technology (Pang et al., 2020).

The third set of factors included moderating factors. Age and novelty-seeking behaviour were argued to be the moderators of the relationships motivation-continuous intention to use and training-continuous intention to use (Dabholkar & Bagozzi, 2002; Um et al., 2020). Additionally, awareness of AI was posited to moderate the relationships such as the relative advantage (of IoMT)-motivation (to use IoMT), the relative advantage, training (to use IoMT), complexity (of IoMT)-motivation, complexity (of IoMT)-training, compatibility (of IoMT)-motivation and compatibility of IoMT-training Chen et al., 2020). The above discussions thus led to the resulting model provided in Fig. 1.

3.2.1 Relative Advantage → (Motivation, Training)

Using DOI the relationship between the relative advantage, training, and the intrinsic motivation of an individual to use IoMT can be established. The relative advantage creates a sense of autonomy in an individual and influences the intrinsic motivation of individuals to use IoMT (Jaleel et al., 2020). Similarly, Park and Choi (2019) argue that training represents organizational factors and can be used as a determinant of the information technology innovation behavioural intention to use IoMT alongside DOI components. Therefore, the following can be hypothesised:

H1a: Relative advantage positively influences motivation.

H1b: Relative advantage positively influences training.

3.2.1. Complexity → (Motivation, Training)

If an innovation is complex, researchers have used different ways to reduce complexity to motivate users. Hardgrave et al. (2003) found out that complexity has a negative relationship with perceived usefulness, a construct of motivation. Similarly, Tristani et al. (2020) argued that more users will embark on training, using learning materials if the material is less complex. That is to say, the complexity and training in IoMT are related. Based on the arguments, the following is hypothesised:

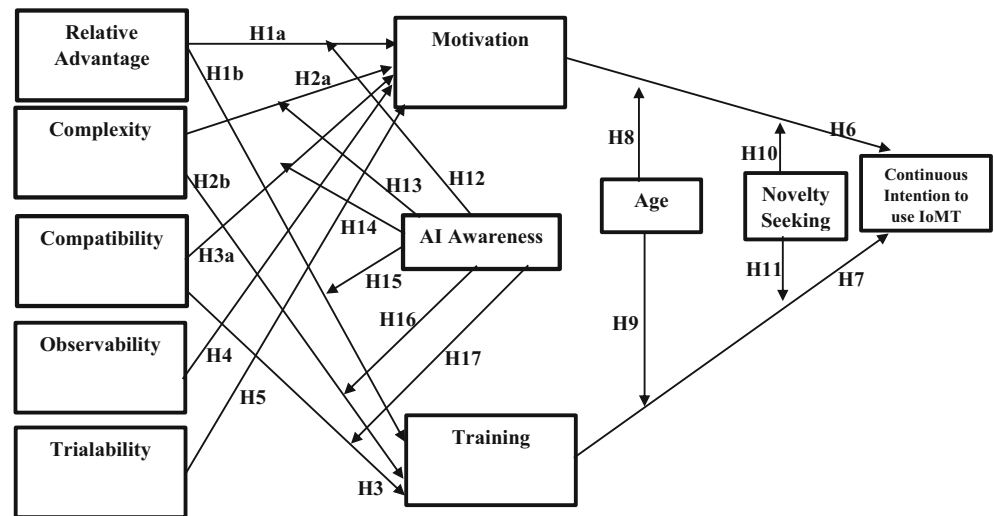
H2a: Complexity negatively influences motivation.

H2b: Complexity positively influences training.

3.2.2 Compatibility → (Motivation, Training)

Innovation adoption rate is related to the degree of compatibility (AlSheibani et al., 2020). Further, if two IoMT devices

Fig. 1 Proposed Research Model (Source: Adapted from Rogers, 1995)



are compatible then the perceived ease of use (synonymous to motivation) (Bastari et al., 2020) could be positively influenced (Agarwal & Prasad, 1999). Additionally, incompatibility could be reduced by training. Thus, replacing perceived ease of use by motivation, the following could be hypothesised:

- H3a: Compatibility positively influences motivation.
- H3b: Compatibility positively influences training-

3.2.3 Observability → Motivation

Observability of innovation is defined as an innovation’s outcome which shows that innovation is noticeable to others (Rogers, 2003; Al-Rahmi et al., 2019;) and is explained by DOI. Taking the recommendations of Al-Rahmi et al. (2019) it is posited that observability (of IoMT) influences motivation. Therefore, we propose the following hypothesis:

- H4: Observability positively influences motivation.

3.2.4 Trialability→ Motivation

Literature shows that trialability (of IoMT) as a diffusion factor affects the motivation of users of the innovation (Al-Rahmi et al., 2019). Based on the arguments of Rogers (2003) and Chiyangwa and (Trish) Alexander (2016) it is posited that success of trialability could reduce uncertainty about IoMT and speedy adoption. Therefore, we propose the following hypothesis:

- H5: Trialability positively influences motivation to use IoMT.

3.2.5 Motivation → Continuous Intention to Use IoMT

Motivation is a personal characteristic and has been found to play an important role in many technologies and innovations’ continuous intention to use IoMT and usage related concepts (Franke et al., 2006; Hang & Kau, 2016; Marzouki & Belkahla, 2019). This was tested as there is no compelling evidence in the literature to establish this. Therefore, we propose the following hypothesis:

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

3.2.6 Training → Continuous Intention to Use IoMT

Literature shows there is a lack of knowledge on how training in IoMT as a concept has to be understood with regard to the use of new technologies (Gaynor et al., 2015; Al-Gahtani, 2016;) including a diffusing technology. Further, where the motivation of individuals is involved, then training becomes an automatic choice, as training is considered to be an associate construct of motivation (Bhatti et al., 2013). Therefore, we propose the following hypothesis:

- H7: Training positively influences continuous intention to use IoMT.

3.2.7 Age as a Moderator of Relationship between Motivation, Training, and Continuous Intention to Use

That age can act as a moderator of relationships in a model that concerns the intention to use technology is supported by UTAUT (Venkatesh et al., 2012). 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. Similarly, it is posited that IoT solutions must be associated with training in order to ensure its effective usage (McRae et al., 2018) including IoMT. Therefore, we propose the following hypotheses:

H8: Age moderates the relationship between motivation to use and continuous intention to use IoMT.

H9: Age moderates the relationship between training and continuous intention to use IoMT.

3.2.8 Novelty Seeking as a Moderator of the Relationship between Motivation, Training, and Continuous Intention to Use

It is argued in the literature (Venkatesh et al., 2012) that novelty seeking behaviour affects the motivation of people and drives the continuous intention to use the technology of users of innovation. Further, by using UTAUT it can be argued that the relationship between facilitating conditions (e.g., training) and intention to use can also be moderated by novelty seeking behaviour of users (Venkatesh et al., 2012). Therefore, we propose the following hypotheses:

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

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

3.2.9 AI Awareness as a Moderator of the Relationship between DOI Constructs and Motivation

IoMT while diffusing is affected by awareness about technology (Leal & Albertin, 2015). Further, the relative advantage of AI in IoMT is the predictability of risk and presence or absence of a disease in an individual (Matheny et al., 2019). When supported by awareness about AI, it could encourage (motivate) users to continuously use IoMT, as AI could reduce the complexities involved in predicting risk and presence or absence of a disease in individuals. Similarly, AI awareness could help IoMT users, for instance, individuals and organisations, who are small and relatively unsophisticated (Matheny et al., 2019) to overcome complexity related challenges concerning IoMT. Finally, compatibility concerns, for instance interoperability concerns of IoMT devices, could be a major problem for the usage of IoMT (Jaleel et al., 2020). Therefore, Chen et al. (2020) argue that AI awareness is

necessary for AI adoption which implies that embedding responsible AI in IoMT needs to be supplemented by AI awareness. Therefore, we propose the following hypotheses:

H12: AI awareness positively moderates the relationship between relative advantage and motivation.

H13: AI awareness positively moderates the relationship between complexity and motivation.

H14: AI awareness positively moderates the relationship between compatibility and motivation.

3.2.10 AI Awareness as a Moderator of the Relationship between DOI Constructs and Training to Use

Training has been already posited to be influenced by the relative advantage in an earlier section. It is also posited that the relationship relative advantage -motivation can be moderated by AI awareness and can be linked to training as motivation is concerned with training (Miao et al., 2020). Next, Chen et al. (2020) argues that training in AI and awareness in AI created due to training can enhance usage intentions reducing complexities. Finally, AI should be compatible with the organisational environment, which in this study is AI embedded in IoMT in a healthcare setting. Therefore, we propose the following hypotheses:

H15: AI awareness positively moderates the relationship between relative advantage and training.

H16: AI awareness positively moderates the relationship between complexity and training.

H17: AI awareness positively moderates the relationship between compatibility and training.

4 Research Methodology

The research was conducted in Bahrain. As far as healthcare is concerned, Bahrain has well-equipped hospitals both in the public and private sectors with 19 hospitals and 746 registered health care facilities operating by the end of 2019 (NHRA, 2019). The healthcare system in Bahrain is very similar to the NHS in the UK. The Internet of healthcare things (synonymous to IoMT) is already being used in the healthcare sector (Haji, 2018) with such devices as wearables widely being used by citizens and their health tracked through the internet by healthcare professionals. All hospitals involved in this research were provided with the ethical approval granted by University of Bradford, which enabled the researcher to mitigate challenges concerning access to subjects who could participate in the research.

4.1 Data Collection

It was pertinent to approach research respondents who were knowledgeable about the phenomenon under investigation. Thus, respondents who have experiences of using IoMT were selected, to provide rich, diverse, and holistic views. A self-administered questionnaire (Appendix B) was developed to collect data through an online survey, by adapting already validated instruments found in the literature. Only closed and multiple-choice questions were included in the questionnaire. The list of healthcare professionals accessed to get responses and their percentage is provided in Table 1.

Section A in the survey instrument was used to collect the demographic information related to gender, age, professional status, education level and the familiarity of the participants with regard to IoMT. Section B in the survey instrument consisted of 49 items that were used to measure the independent and dependent variables (Table 2).

4.2 Survey Protocol

A survey protocol was developed to ensure that the process of generating the data was structurally sound. 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’. Appendix B lists the items used to measure the variables. Random sampling was used to collect data. The total population of healthcare professionals who are available in Bahrain was estimated to be over 15,000. The sample size worked out to be 375 at a confidence level of 95% and a confidence interval of 5%. Considering the fact that the minimum sample size of participants from whom data needs to be collected was calculated as 375, a little over 500 respondents were

approached with the support of many hospitals in Bahrain. To maintain anonymity, the names of the hospitals have not been mentioned in this paper. 276 responses were received which is a response rate of 55.2%. Sekaran and Bougie (2016) recommend that a response rate of 30% is acceptable in most research efforts using a survey. Eight responses were rejected as the responses were not complete. Thus, the final number of useful responses stood at 268. Another 34 responses were rejected as outliers. Outliers were detected using Mahalanobis distance and were deleted. Table 2 shows the details of the demography of the participants. In addition, descriptive statistics are provided in Table 3. The standard deviation for all items was found to be less than ±1.5 indicating the normal distribution of data.

5 Findings

The analysis was conducted using SPSS and AMOS version 21.0. This constitutes of two steps including the confirmatory factor analysis and the structural model analysis.

5.1 Confirmatory Factor Analysis

SPSS (Version 21) was used to analyse reliability of the instrument and the scale. Cronbach’s alpha is a widely used test to determine the reliability of the scale and provides an estimate of the internal consistency of the items used to measure the constructs (Cronbach, 1946; Sekaran & Bougie, 2016). Sekaran and Bougie (2016) explain that an alpha value >0.7 is considered to be acceptable.

The internal consistency measurements showed that item to item correlations and item to total correlations were acceptable for all constructs with the minimum for any construct found to

Table 1 List of healthcare professionals who participated in the survey

Occupation of healthcare professionals	#	%
Hospital doctors	29	10.51
Community Health Services doctors	1	0.36
Consultant doctors	45	16.30
General practitioners	20	7.25
Allied healthcare professional	30	10.87
Pharmacist	13	4.71
Healthcare scientist (e.g., cervical cytology screener, phlebotomist, new-born hearing screener and healthcare science assistant/associate)	3	1.09
Nurses and Health Visitors	75	27.17
Ambulance staff	1	0.36
Other GP Practice staff (direct patient care) (e.g., other staff involved in providing direct patient care, which includes clinical pharmacists, dispensers, phlebotomists, therapists, healthcare assistants and others).	27	9.78
Other GP Practice staff (admin) (e.g., Receptionist and administrative staff)	32	11.59
Total	276	100.00

Table 2 Demographic characteristics of respondents

Variables	Specification	Frequency	Valid Percent
Gender	Male	160	60.4
	Female	90	33.6
	Prefer not to say	16	6
Age	18–25	23	8.6
	26–33	88	32.8
	34–41	59	22
	42–49	43	16
	Over 50	55	20.5
Usage	Using IoMT currently	69	25.7
	Aware of IoMT	77	28.7
	Intend to use IoMT in future.	30	11.2
	Not familiar with IoMT	92	34.3
Education	High school graduate or equivalent	6	2.2
	Bachelor's degree	129	48.1
	Master's degree	64	23.9
	Professional certificate	48	17.9
	Doctorate	21	7.8
Occupation	Hospital doctors	28	10.4
	Community Health Services doctors	1	0.4
	Consultant doctors	45	16.8
	General practitioners	19	7.1
	Allied healthcare professional	28	10.4
	Pharmacist	12	4.5
	Healthcare scientist	3	1.1
	Nurses and Health Visitors	72	26.9
	Ambulance staff	1	0.4
	Other GP Practice staff (direct patient care)	27	10.1
Other GP Practice staff (admin)	32	11.9	

be 0.397 and 0.536, respectively. One item (NS5: “I do not like meeting IoMT service providers who have new ideas about IoMT”) measuring the construct novelty seeking was found to cause correlational problems and was deleted. The convergent validity was established through the inter-item correlation and item to total correlation which according to Robinson et al. (1991) should be greater than 0.3 and 0.5, respectively. The descriptive statistics showed that the standard deviation figures of all the items were within ± 2.0 indicating that the responses were normally distributed. Structural Equation Modelling (SEM) was used to analyse the data to test the hypotheses and answer the research question. This is a widely used technique that is used to estimate a set of interrelated dependence relationships simultaneously (Hair et al., 2006). The confirmatory factor analysis led to the final structural model given in Fig. 2. Fitness of the CFA model to data was tested using Comparative Fit Index (CFI), Incremental Fit Index (IFI) and Root Mean Square Error of Approximation (RMSEA). According to literature there is no specific number of indices that need to be tested and reported (Schermele-

Engel et al., 2003). However, Karakaya-Ozyer and Aksu-Dunya (2018) recommend that it is important to report as many model fit indices as possible although the choice of the fit indices is left to the researchers. According to Schreiber et al. (2006) minimum values of CFI and IFI considered as acceptable is >0.9 . According to Hooper et al. (2008) acceptable values of RMSEA lie between 0.05 and 0.1 (Gul & NezamiFar, 2020). The fit indices derived from AMOS were CFI = 0.905; IFI = 0.906; and RMSEA = 0.074 (see Table 4).

5.2 Applying the Structural Model

The structural model is provided in Fig. 1. The structural model was used to test the relationship between the exogenous (relative advantage, complexity, compatibility, trialability and observability) and endogenous variables (motivation, training, and continuous intention to use IoMT). The moderation variables were not included in the structural model. The analysis of the

Table 3 Alpha, mean and standard deviation of constructs

Construct	Cronbach’s alpha	Items	Mean	S.D.
Relative advantage	0.950	RA1	3.7039	1.11913
		RA2	3.6609	1.11459
		RA3	3.7124	1.10978
		RA4	3.5923	1.06728
		RA5	3.4764	1.11053
		RA6	3.5150	1.10289
Complexity	0.854	CPX2	2.5279	1.06688
		CPX3	2.6137	1.08126
		CPX4	2.6824	1.07177
Compatibility	0.837	CMP1	3.1760	1.02928
		CMP2	3.2618	1.04020
		CMP3	3.4635	1.00417
		CMP4	3.3820	0.95368
Triability	0.848	TRI1	2.8755	1.12838
		TRI2	2.9442	1.11470
		TRI3	2.9571	1.16628
		TRI4	2.7639	1.12575
Observability	0.801	OBS1	3.0730	1.12908
		OBS3	3.0086	1.11026
		OBS4	2.9528	1.13426
Training	0.948	TRN1	3.0429	1.08986
		TRN2	3.1288	1.10668
		TRN3	3.2833	1.15091
		TRN4	3.2403	1.13438
		TRN5	3.2403	1.09965
Motivation	0.916	MOT1	3.5966	1.09481
		MOT3	3.4034	1.05061
		MOT4	3.4721	1.05059
		MOT5	3.4378	1.10514
Continuous intention to use IoMT	0.922	CI1	3.7210	1.13119
		CI2	3.7983	1.11324
		CI3	3.7082	1.01742
		CI4	3.7339	1.08179

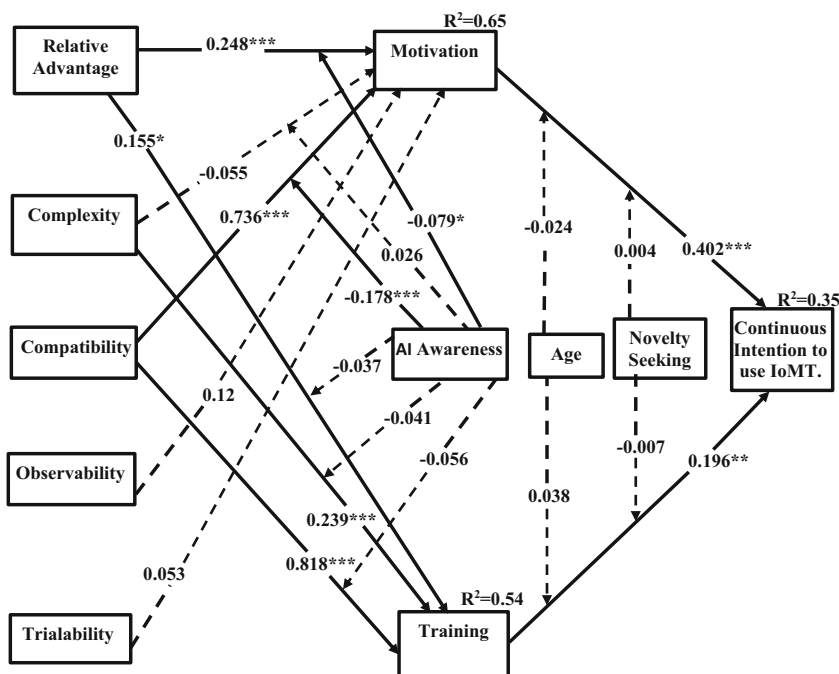
influence of moderating variables age, AI awareness and novelty seeking on the different relationships were separately tested using AMOS. The construct reliability was established by the squared multiple correlation

(SMC) with all values found to be greater than 0.3 which is recommended by Holmes-Smith *et al.*, (2006). Discriminant validity was established using sample correlations. Correlations between latent constructs

Table 4 Fit indices for measurement model

Fit statistics	Recommended value	Measured value
Chi-square/ Degree of Freedom (CMIN/DF)	< 3.000	2.274
Probability value (p)	> 0.05	0.000
Incremental fit index (IFI)	≥0.9	0.906
Comparative fit index (CFI)	≥0.9	0.905
Root mean square error of approximation (RMSEA)	≤0.080	0.074

Fig. 2 Structural model with regression weights



or observed variables (items) higher than 0.80 or 0.90 suggest the presence of discriminant validity (Holmes-Smith et al., 2006). The highest value of correlation (0.893) was found between the two items TRN4 and TRN5. Thus, discriminant validity was established.

Final valid relationships are provided by the AMOS output provided in Table 5. Fitness of the model was tested using CFI, IFI and RMSEA (Table 6).

After checking the fitness of the model, the next test conducted was the average variance extracted test which provides another measure of discriminant validity as well as indicates the presence or absence of method bias. The results presented in Table 7 show that the discriminant validity extracted for all the constructs has been achieved.

5.3 Moderation Effect by AI Awareness

Moderation of the various paths by AI awareness was tested using AMOS. The following example provides the method used.

AI Awareness moderating the relationship Relative Advantage → Motivation

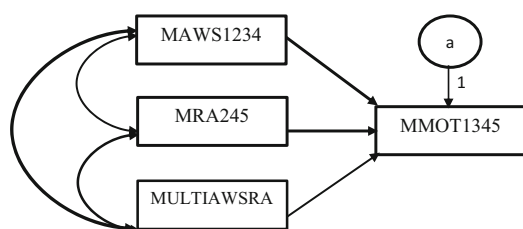


Fig. 3 Moderation effect of AI Awareness

5.4 AI Awareness moderating the relationship of Relative Advantage → Motivation

Here MMOT1345 indicates the mean of the items measuring the construct motivation, MAWS1234 indicates the mean of the items measuring the construct AI Awareness, MRA245 indicates the mean of the items measuring the construct relative advantage and MULTIAWSRA indicates the multiplication of MAWS1234 and MRA245. In order to test the moderation effect of AI Awareness on the relationship between Relative Advantage and Motivation, the influence of the variables MAWS1234, MRA245 and MULTIAWSRA on the construct motivation was measured using AMOS. The regression weights report of AMOS is provided in Table 7. The main parameter of interest was the p value of the product term MULTIAWSRA. Table 8 shows that the p value is less than 0.05 indicating that the influence of the product term on motivation is statistically significant. Thus, the hypothesis H15 is accepted. Table 9 shows the explanation of the coding adopted in this research with regard to moderators. A similar test was conducted to verify the moderation effect of AI Awareness on other paths, the results of which are provided in Table 10.

5.5 Moderation Effect by Novelty Seeking and Age

Novelty seeking behaviour of users of IoMT was not found to influence the relationship between motivation and training to use IoMT on the one hand and continuous intention to use IoMT on the other. This was revealed when novelty-seeking behaviour was used as a moderating variable of the

Table 5 List of hypotheses accepted and rejected

Path relationship			Path coefficient	p value	Accepted hypotheses	Dependent Variable	R ²
Motivation	<--	Relative advantage	0.248	***	H1a	Motivation	0.65
Training	<--	Complexity	0.239	***	H2b	Training	0.54
Motivation	<--	Compatibility	0.736	***	H3a	Continuous intention to use	0.35
Training	<--	Relative advantage	0.155	.023	H1b		
Training	<--	Compatibility	0.818	***	H3b		
Continuous intention to use	<--	Motivation	0.402	***	H6		
Continuous intention to use	<--	Training	0.196	0.002	H7		
Rejected hypotheses							
Motivation	<--	Complexity	-.055	0.320	H2a		
Motivation	<--	Trialability	.053	0.597	H4a		
Motivation	<--	Observability	0.12	0.28	H5a		

***indicates that the regression weight for the predictor in the predicted is significantly different from zero at the 0.001 level (two-tailed)

relationship between motivation and training on the one hand and continuous intention to use IoMT on the other, using AMOS as in the case of AI Awareness. The results of the regression showed that there was no statistical significance found when the product terms (mean novelty-seeking * mean of motivation) and (mean of novelty-seeking * mean of training) were regressed with continuous intention to use. Thus, hypotheses H10 and H11 were rejected. Through the same process, it was found that age did not moderate the relationships (motivation) → (Continuous intention to use IoMT) and (training) → (Continuous intention to use IoMT). Thus, hypotheses H8 and H9 were rejected.

5.6 Total Effect of Independent Variables on Dependent Variables

The total effect of independent variables on the dependent variables through different paths provide an idea about the influence exerted by the independent variables on the dependent variable. It also enables an understanding of the predictability of the continuous intention to use IoMT (Table 11).

The finally specified model that has been tested fully is provided in Fig. 2. The solid lines indicate the accepted relationships while the broken lines indicate the rejected

relationships. Thus, in the final model it can be seen that only 9 hypotheses have been accepted.

6 Discussion

The main aim of this research was to investigate the continuous intention to use IoMT by healthcare professionals characterized by responsible AI and factors that affect it. IoMT is an innovation of recent times and is still evolving (Kamilaris & Botteghi, 2020). The theory of DOI was applied to explain the phenomenon of continuous intention to use IoMT. DOI explained the diffusion of two interrelated innovations namely IoMT embedded with responsible AI.

The relative advantage drives motivation and training, which in turn influences continuous intention to use IoMT positively. For instance, IoMT can help in remote monitoring of patient health. Healthcare professionals are often constrained to be at the place of the patient due to many factors including culture, language barrier, accessibility, and workload (Al-Hadban et al., 2017; Jacob et al., 2020). Additionally, training in IoMT will help healthcare professionals to deliver better healthcare which in turn is expected to motivate them, an

Table 6 Fit indices for structural model

Fit statistics	Recommended value	Measured value
Chi-square/ Degree of Freedom (CMIN/DF)	< 3.000	2.427
Probability value (p)	> 0.05	0
Incremental fit index (IFI)	≥0.9	0.915
Comparative fit index (CFI)	≥0.9	0.914
Root mean square error of approximation (RMSEA)	≤0.080	0.078

Table 7 Discriminant validity

	RA	CMP	TRI	CI	OBS	TRN	MOT	CPX
RA	0.826							
CMP	0.310	0.615						
TRI	0.180	0.236	0.619					
CI	0.585	0.284	0.171	0.773				
OBS	0.143	0.259	0.428	0.132	0.650			
TRN	0.240	0.345	0.401	0.205	0.561	0.832		
MOT	0.368	0.445	0.229	0.261	0.259	0.355	0.805	
CPX	0.001	0.014	0.063	0.000	0.045	0.063	0.003	0.664

argument supported by Tu (2018). The results are in line with the relevant literature (Al-Rahmi et al., 2019). Similar arguments could be extended to the concepts of compatibility, the complexity, observability and trialability. Compatibility influences continuous intention to use IoMT through motivation (regression estimate 0.743) and training (regression estimate 0.85) positively. Compatibility has a large correlation with motivation and training.

Complexity was found to influence continuous intention to use IoMT positively through training to use IoMT. Trialability and observability were not found to have any significant relationship with motivation to use IoMT. The complexity, e.g., lack of skilled staff to manage a multivendor environment (Haddud et al., 2017), can affect motivation of users. The results show further that training (regression estimate 0.244) influences continuous intention to use by overcoming complexities. When this result is combined with the compatibility, then it can be seen that higher compatibility motivates the healthcare professionals while higher complexity does not motivate the users (this explains the rejection of hypothesis H2a). The explanation for this may be that IoMT trials or observations about how to use IoMT in healthcare settings are seldom useful. This explains why the connections between trialability and motivation, as well as observability and motivation, were found to be statistically insignificant (this explains the rejection of H4a and H5a). The above observations

Table 8 Moderation effect

		Estimate	S.E.	C.R.	P
MMOT1345	<--- MAWS1234	0.748	0.134	5.591	***
MMOT1345	<--- MRA245	0.579	0.099	5.831	***
MMOT1345	<--- MULTIAWSRA	-0.079	0.034	-2.316	0.021

Table 9 Coding of moderated and moderating variables

Code	Construct
MAWS1234	Mean AI Awareness
MRA245	Mean Relative advantage
MCPX23	Mean Complexity
MCMP1234	Mean Compatibility
MMOT1345	Mean Motivation
MTRN	Mean Training
MULTIAWSRA	Multiply: (MAWS1234 * MRA245)
MULTIAWSCPX	Multiply: (MAWS1234 * MCPX23)
MULTIAWSCMP	Multiply: (MAWS1234 * MCMP1234)

are in line with the findings of others (Jalo et al., 2020; Vagnani & Volpe, 2017).

Furthermore, the overall effect (Table 10) of relative advantage, complexity, and compatibility influence indirectly continuous intention to use IoMT positively (regression estimates 0.14, 0.363 and 0.037 respectively). The results could be interpreted in a way that compatibility is the most significant DOI factor that helps in the diffusion of IoMT followed by its relative advantage. Complexity appears to have no specific significance in enhancing continuous usage when considered as part of the total effect of independent variables.

Regarding the moderators, it can be seen that age was not found to be correlated with any of the constructs, namely motivation, training and continuous intention to use IoMT. Similar results are reported by others in the literature (Cabeza-Ramírez et al., 2020; Rajmohan & Johar, 2020) confirming that the current research outcomes are in line with others' findings. Novelty seeking behaviour of healthcare professionals was also found to be not moderating the relationships between motivation, training and continuous intention to use IoMT. Similar findings have also been reported by other researchers (Andreasen & Streukens, 2013; Hsiao & Yang, 2010).

Finally, AI awareness as a moderator was found to positively influence the relationships, namely the relative advantage to motivation (regression estimate -0.079) and compatibility (regression estimate -0.178) to motivation negatively. That is to say, the higher the AI awareness, the influence of relative advantage and compatibility will be lower on the motivation. This result is a new finding. This signifies that if AI moderates the diffusion of IoMT, then the relevance of relative advantage and compatibility could diminish making the use of IoMT more automatic and less difficult to use on the part of the healthcare professionals, thus increasing the use of IoMT and motivating users to integrate IoMT in their practice (Abubakar & Ahmad, 2013).

Table 10 Regression results of moderation

Moderated relationship	Moderator	Multiplication factor	Regression estimate	R ²	p value	Hypothesis	Accepted?
RA→MOT	MAWS1234	MULTIAWSRA	−0.079	55%	0.021	H12	Accepted
CPX→MOT	MAWS1234	MULTIAWSCPX0	.026	–	0.496	H13	Rejected
CMP→MOT	MAWS1234	MULTIAWSCMP	−0.178	60%	***	H14	Accepted
RA→TRN	MAWS1234	MULTIAWSRA	−0.037	–	0.287	H15	Rejected
CPX→TRN	MAWS1234	MULTIAWSCPX	−0.041	–	0.237	H16	Rejected
CMP→TRN	MAWS1234	MULTIAWSCMP	−0.056	–	0.159	H17	Rejected

6.1 Theoretical Contributions

Application of DOI to understand the diffusion of innovation is widely found in the literature for a single innovation at a single point of time (AlSheibani et al., 2020; Sayginer & Ercan, 2020; Tran & Cheng, 2017). However, when two interrelated innovations diffuse at the same time with the possibility of recurrent innovation underuse, whether DoI as a theory could be applied or not is clear in the literature. This implies that when a responsible AI as innovation is embedded in IoMT (another innovation), then how to explain the adoption rate or continuous use of IoMT is a major area not covered in the literature. Lin (2021) argues that DOI can address only single innovations diffusing and adopting at one time. However, there is evidence in the literature to show that researchers have combined more than one theory at a time to explain either adoption intentions (Stokey, 2020; Tran & Cheng, 2017) or continuous intention to use (Huang et al., 2020).

However, research outcomes that explain the concurrent diffusion of two innovations and their influence on continuous intention to adopt in the presence of recurrent innovations (like earlier versions of IoMT or earlier versions of AI) using DOI are not found in the extant literature. This research has provided insight into expanding Rogers’ (2003) model to explain two interrelated innovations diffusing at the same time. Results of the research have shown that DOI factors relative advantage, complexity and compatibility determine continuous intention to use IoMT embedded with responsible AI through behavioural attributes motivation and

training. At the same time responsible AI represented by AI awareness is seen to moderate the relationship between the determinant and the behavioural attributes. Thus, the IoMT is depicted as the determinant while responsible AI is depicted as the moderator. This implies that a new and novel extension of Rogers’ (2003) DOI model was derived in this research that can explain the concurrent diffusion of two interrelated innovations. This is the case even when the recurrent use of the innovations could be taking place which is signified by the continuous intention to use the innovation. This theoretical extension was validated by showing the variance introduced in motivation, training and continuous intention to use IoMT by the determinants to the extent of 65%, 54% and 35% respectively. Similarly, the extent of moderation by AI awareness of the valid relationships between relative advantage and compatibility on the one hand and motivation on the other is shown to be 55% and 60% respectively. These measurements confirm the theoretical implications of this research.

6.2 Practical Implications

The research outcomes have important implications for the healthcare practitioners. The research provides a realistic and parsimonious method to predict the continuous intention to use IoMT that is constructed with responsible AI. Improving motivation to understand AI and training to use IoMT associated with AI responsibility when IoMT is still diffusing is a plausible and practical solution that can allow healthcare professionals to continuously use it.

Table 11 Total effect of independent variables on the dependent variable

	Complexity	Compatibility	Relative advantage	Training	Motivation
Training	0.239	0.818	0.155	0.000	0.000
Motivation	−0.055	0.736	0.248	0.000	0.000
Continuous intention to use IoMT	0.024	0.456	0.130	0.196	0.402

The study shows that compelling relative advantage can motivate healthcare professionals to use IoMT and influence them to get trained to overcome the complexity of using it. The results point out that compatibility is an important driver of both motivation and training to use IoMT. While prior studies hypothesise that users are often intimidated by complex technologies and innovations such as AI and IoMT when it comes to their continuous use, our study negates this assumption. In a healthcare context, both observability and trialability were not related to motivation to use IoMT implying that users do not consider it a need to observe others using the technology or get an opportunity to try it out before using it. Furthermore, results showed that AI awareness is an important moderator of the relationship between the complexity and the motivation.

Since IoMT is a technology-based solution, it is usual that such technological solutions continuously change with innovations released frequently with upgraded technology making the continuous usage of IoMT a concern. However, the results of this research clearly show that diffusion factors such as relative advantage, compatibility, and complexity alongside the responsible AI influence behavioural traits motivation and training, can provide a predictable model that could be used to enhance continuous intention to use IoMT. In addition, the results show that novelty seeking behaviour and age do not affect the diffusion of AI based IoMT. These findings imply that despite risks, problems of ethics and challenges associated with AI, healthcare professionals could continuously use IoMT by improving their motivation and training to use IoMT.

6.3 Limitations and Future Research Directions

The main limitation of this research has been the use of isolated examples of moderators found in the literature and restricting the determinants to the ones defined by the theory of DOI. Had there been additional determinants there was a possibility that the results of this research could have been different. For instance, perceived enjoyment to use IoMT could be a determinant (Al-Rahmi et al., 2019). Approaching hospitals and healthcare professionals to collect data was challenging as those professionals were completely involved in fighting COVID-19. Challenges included summary rejection to participate in the survey to the risk of contracting COVID-19 by the researcher due to the proximity of some officials of hospitals when approached to gain access to the healthcare professionals. This reduced the number of participants to some extent. In non-COVID-19 environment, better participation of subjects and the research outcomes

could have been different. Furthermore, the current research was conducted in one country and replicating the research in other countries could provide different outcomes (Kumar et al., 2018; Obeidat et al., 2020; Patil et al., 2018a; Rana et al., 2014, 2015; Williams et al., 2016). The future research can also apply the more advanced theory of adoption and diffusion of IoMT such as UTAUT (Dwivedi et al., 2019) and UTAUT2 (Tamilmani et al., 2021) and could come up with some more relevant constructs using the meta-analysis of such theories as well (Patil et al., 2018b).

7 Conclusion

The study examined the contradictions caused by AI being risky and complex technology that could easily dissuade healthcare professionals from using an AI based IoMT that promises improved healthcare to patients. From the results obtained in this research the following conclusions can be derived. Continuous intention to use IoMT is determined by DOI factors relative advantage, complexity, and compatibility, but indirectly through the mediators namely motivation and training to use IoMT. Continuous diffusion of AI based IoMT can lead to continuous intention to use IoMT by healthcare professionals. Awareness about AI provides knowledge about the problems including ethical and moral ones, that could be caused by AI. Motivation and training to use IoMT can enable the healthcare professionals to successfully handle the risks and complexities associated with AI leading to the responsible use of IoMT. Continuous intention to use IoMT occurs while the AI based IoMT is still diffusing. Continuous intention can also be predicted using relative advantage, complexity, and compatibility in the presence of two interventions and a moderator. Managers in healthcare settings now have a model to deal with problems caused by a risky and complex AI based IoMT. In those situations, it is possible to address the risks involved by motivating and training healthcare professionals in AI, thus avoiding complex situations that could lead to unethical decision making of healthcare professionals. Additionally, the model provides evidence on the necessity to exploit the relative advantage, compatibility and complexity of an AI based IoMT which in turn could motivate healthcare professionals to use AI based IoMT continuously. Finally, it can be concluded that the outcome of this research provides a rich knowledge on the utility and application of AI based IoMT but also under less severe circumstances.

Appendix A Definitions of constructs and items constituting them

Variable/Construct	Definition	Source
Relative advantage	The degree to which an innovation is perceived as better than the idea it supersedes.	Rogers (1995)
Compatibility	The degree to which an innovation is perceived as being consistent with the existing values, past experiences, and needs of potential adopters.	Rogers (1995)
Complexity	The degree to which an innovation is perceived as being difficult to use	Rogers (1995)
Observability	The degree to which the results of an innovation are visible to others	Rogers (1995)
Trialability	The degree to which an innovation may be experimented with on a limited basis before behavioural intention to use IoMT	Rogers (1995)
Novelty seeking	Novelty seeking means to seek knowledge about new products or item which are created & tested on adult users or customers. Novelty seeking as a personality trait expressing excitement in reaction to new stimuli.	Manning et al. (1995) Cloninger et al. (1991)
Age	Age is major contributor to the understanding of the behavioural intention to use technology of people.	Martins et al. (2018)
AI awareness	Awareness is a form of knowledge that can be acquired actively or passively.	Rogers (2010)
Motivation	Motivation has been defined as an emotion or desire operating on the will and causing it to act.	Randall et al. (2006)
Training	Training is the degree to which trainees effectively apply the knowledge, skills, and attitudes gained in a training context to the job.	Baldwin and Ford (1988)

Items for various constructs

Code	Item	Source
CI1	Given the chance, I intend to use IoMT applications	Venkatesh (2000); Venkatesh et al. (2012)
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	
RA1	Using an IoMT application enables me to complete tasks faster.	Savoury (2019); Al-Rahmi et al. (2019); Moore and Benbasat (1991)
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.	
COMPLEX1	The use of IoMT requires a lot of mental effort	Oliveira et al. (2014)
COMPLEX2	The use of IoMT is frustrating	
COMPLEX3	The use of IoMT is too complex for business operations	
COMPLEX4	The skills needed to adopt IoT are too complex for employees of the firm	
COMPAT1	Using an IoMT is compatible with all aspects of my work.	Savoury (2019); Al-Rahmi et al. (2019); Moore and Benbasat (1991)
COMPAT2	Using an IoMT is completely compatible with my current situation.	
COMPAT3	I think that using an IoMT fits well with the way I like to work.	
COMPAT4	The use of IoMT is fully compatible with the value system of my workplace	
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.	

(continued)

OBS1	I have seen what others do while using IoMT.	Al-Rahmi et al. (2019); Moore and Benbasat (1991)
OBS2	In my organization, 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	
TRAIN1	My performance was satisfactory on the IoMT application training	Alias et al. (2019); Saks and Haccoun (2007);
TRAIN2	I was able to achieve the objectives of IoMT application training	Noe (2010)
TRAIN3	I could learn as much as possible from the training on IoMT	
TRAIN4	I was able to benefit from the training on IoMT	
TRAIN5	The training on IoMT significantly added to my knowledge	
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	
NS1	While using IoMT, I am always seeking new ideas about IoMT	Mehrabian and Russell (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	
MOT2	I think it is interesting	Guay et al. (2000); Vallerand et al. (1989)
MOT1	My job requires me to do it	
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	

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