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Scepticism and Resistance to IoMT in Healthcare: Application of Behavioural Reasoning Theory with Configurational Perspective

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Abstract: The innovative application of smart devices in healthcare promotes real-time sensing, enables intelligent services, and accelerates medical progress, which ultimately boosts clinical trial efficiency, timely diagnostics, and effective patient-centred care. Despite its proven capabilities, the Internet of Medical Things (IoMT) can flourish only if users in the medical sector willingly use these devices in their daily routine work. Drawing on behavioural reasoning theory and its implication in explaining user behaviour, this study aims to shed light on hospital practitioners' reasons for and against resistance to IoMT. We proposed an integrative theoretical framework that combines system, information, and individual positive and negative factors to understand and explain clinical users' scepticism and resistance toward IoMT. We benefit from a multi-analytical approach including symmetrical (net effect) and configurational analysis to test this theoretical framework. Our study contributes to the literature by proposing new insights into IoMT users' decision-making, considering a dual approach that simultaneously explains positive and negative pathways toward scepticism and resistance. Empirically, this study advances knowledge of users' resistance rationality that could lead to improved managerial policies for introducing and successfully implementing IoMT technologies in hospitals.

Keywords: Internet of Medical Things (IoMT); Resistance; Behavioural reasoning theory; Scepticism; Configurational analysis

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1. Introduction

Human history has shown that with any crisis, new opportunities and ways of doing things emerge. COVID-19 pandemic is one of the tipping points in history that all the people across the world are experiencing. This health crisis could lead to a new era of organising and restructuring organisations, institutions, or even governments through the development and leveraging of digital technologies such as the Internet of Things (IoT), artificial intelligence, Big Data, and Blockchain. Global institutions have reported that in countries like South Korea where digital technologies have been profoundly utilized, the COVID-19 outbreak has successfully slowed down and millions of lives have been saved (WEF, 2020). Compared to some other countries like Italy, South Korea has applied technological innovations (e.g., IoMT) to detect and monitor infected people through real-time information and intelligence in order to quarantine and prevent the escalation of this health crisis (Euractiv, 2020).

Over the last decades, the healthcare industry has been continually embracing digital technologies to help patients with their health issues, support physicians with their tasks, and accelerate workflows in hospitals to provide increased transparency and efficiency. IoT as an emerging technology refers to a network of physical objects of all types and sizes (Patel & Patel, 2016). IoT enables real-time sensing and communicating data and advances intelligent services, envisioning an interconnected, worldwide network of smart devices (Delgosha et al., 2021; Kim & Kim, 2016). Similar to other industries, healthcare is increasingly realising the transformative capabilities of IoT related technologies like IoMT (Internet of Medical Things). IoMT innovative applications are used to connect medical devices, capture and transmit medical data, and improve safety and efficiency in society and healthcare. It is estimated that the total value of the IoMT market grows from $113 billion in 2019 to $332 billion by 2027, with a compound annual growth rate of 13.2% (Allied Market Research, 2020).

IoMT has tremendous potentiality in improving diagnosis and treatment, enhancing patient experience, saving costs, and reinforcing the disease management process. However, this technology would be successfully integrated into the healthcare processes only if healthcare practitioners willingly adopt and use these devices in their work routines. In a study conducted by Deloitte 71% of 237 respondents working in the IoMT industry believe that the healthcare providers and clinicians are not ready to utilise IoMT generated data (Haughey et al., 2018). Furthermore, Cisco (2017) reported that approximately 75% of IoT projects failed and emphasised that the 'human factor' is the most salient cause behind the success or failure of these projects. Accordingly, our empirical research attempts to understand the main reasons influencing the human factors' (healthcare providers') scepticism and resistance toward using IoMT.

IoT related technologies, as breakthrough innovations are experiencing dramatic growth in various industries like healthcare, yet, IoMT ultimate success mostly relies on its adoption by prospective users (Martínez-Caro et al., 2018). While the IoMT market is growing, the research is still in its infancy stages (Brous et al., 2020). Specifically, it is necessary to understand and explain the main reasons that promote or hinder the adoption/resistance of IoMT users' behaviours. Prior studies have identified influential factors that determine the resistance toward healthcare information technology as a generic concept (e.g. Bhattacherjee, & Hikmet, 2007; Greenhalgh et al., 2014; Nilsen et al., 2016; Mani & Chouk, 2018). Based on these studies, technology-related factors (perceived usefulness, perceived ease of use, perceived compatibility, and perceived threats) (Bhattacherjee, & Hikmet, 2007; Greenhalgh et al., 2014), besides users-related conditions (status quo bias), and organisational conditions (culture and technology introduction policies) are determinants for users' behaviour. Although the literature has provided general valuable insights on antecedents of users' behaviour in healthcare information systems, there is more to learn about IoMT as an emerging technological trend in the healthcare industry. More importantly, the extant literature on IT healthcare resistance has merely focused on the ***enablers*** of resistance. However, meticulously understanding a behaviour needs considering its ***inhibitors*** as well (Delgosha & Hajiheydari, 2020), which are not necessarily the opposite of the enablers (Cenfetelli & Schwarz, 2011). We thus propose that IoMT with its distinctive specifications necessitates a specially designed study to investigate both reasons for and against resistance from the healthcare practitioners' perspective.

Previous studies on resistance towards innovative technologies are primarily based on Ram and Sheth's (1989) framework, which is limited to functional and psychological barriers, or more recently Mani and Chouk's (2018) structure that added individual barriers. These studies have largely overlooked the inhibitors of resistance or simply consider them as just the opposite of enablers. However, more recent research recognises that considering only enablers or inhibitors separately would result in an incomplete or fragmented understanding of users' behaviours (e.g., Cenfetelli et al., 2011; Delgosha & Hajiheydari, 2020). Therefore, it is essential to simultaneously take into account both drivers and hindrance of scepticism and resistance. To fill this gap, this study applies behavioural reasoning theory to respond to RQ1: What are the reasons for and reason against scepticism and resistance toward IoMT technology from healthcare practitioners' view?

Furthermore, research on resistance has used linear, net effects, symmetrical modelling, while user resistance illustrates asymmetric behaviours (Hsieh & Lin, 2018) that are influenced by mutual impacts of enablers and inhibitors (Cenfetelli, 2004). With this realisation, our study aims to address RQ2: How reasons for and reasons against alone and in combination predict scepticism and resistance toward IoMT technology? To tackle these research questions, this study proposes and tests an integrated framework to understand the reasons for and against resistance. Our model covers system, information, and individual-related factors in both positive and negative paths toward IoMT scepticism and resistance. The primary objective of this study is thus to provide a deeper understanding of the reasons for IoMT resistance in a dichotomous mode (reasons for and reasons against) while concentrating on healthcare providers.

We delve into the theoretical background and conceptual model in the next part of the paper, and then we explain the methodology and the analysis results. This paper ends by presenting the discussion and conclusion.

2. Theoretical Background

2.1. IoMT as an emerging technology

As medicine and healthcare have always been at the forefront of using emerging technologies, applying IoT related technologies is also a fast-growing trend in this field. From smart monitors to patient diagnostic machines, radical solutions are being launched to address healthcare challenges (Dua, 2019). It is predicted that in the near future the way the healthcare industry embraces IoT would dramatically shift with the increasing integration of AI and big data into healthcare operations (Haughey et al., 2018). IoMT is a special use case of IoT, referring to the connected system of medical devices and applications that generate, collect, analyse and transmit data to other healthcare IT systems through digital networks. IoMT brings increased connectivity to health systems, enables new and enhanced services for patients, and accelerates medical progress. The unique IoMT capabilities in health data management, connectivity, and superior workflows create value in three ways. First, real-time and precise data from smart healthcare devices would facilitate clinical trial efficiency and improves treatment. Second, enhanced connectivity supports more timely diagnostics and care. Third, streamlined workflows and task automation (Adarsha et al., 2019) enhance the operational productivity of hospitals and encourage patient-centred care. Altogether, advanced and efficient applications of IoMT enable the delivery of 4P in medicine: predictive, preventive, personalised and participatory (Hood & Flores, 2012).

Simply, IoMT is the application of IoT technologies in the healthcare domain. It combines medical devices with cloud-based data management solutions, and automated sensing and monitoring techniques. This technology enables users and healthcare providers' connectivity to create a 'connected health' system that ultimately enables better outcomes in care. There are very wide ranges of IoMT applications from consumers' applications such as wearable devices and remote health monitoring to more institution-based applications such as smart healthcare and Internet-based health services.

Amongst wide ranges of IoMT from smart wearables to smart hospitals, in this study, we focus on clinical applications of smart and connected devices that offer new opportunities to improve the patient experience. Healthcare providers increasingly are using connected devices for sensing, collecting and communicating electronic healthcare records. These devices facilitate real-time patients' data management and thus improve healthcare service delivery. In line with hospital digitalization movements and considering the infancy but rapidly growing IoMT use, we expect an increasing trend in continuous health monitoring devices and telemedicine applications in hospitals (Adhikary et al., 2019). We also discuss that successfully implementing IoMT in hospitals would enhance patient remote monitoring and patient-centric care, as it facilitates real-time data transfer and updates from connected devices.

2.2.Behavioural Reasoning Theory

Reasons theory posits that reasons motivate behaviour as they enable individuals to justify and defend their decisions (Westaby & Fishbein, 1996). Thus, the general assumption is that reasons for performing a behaviour and reasons against it simultaneously can explain an individual's specific motives (Westaby & Fishbein, 1996). In fact, people use reasons to rationalize their actions; they perform a behaviour because they have the desire to reach a goal and use justifiable reasons for pursuing it. According to reason theory, people can logically justify and defend their actions by reason. Hence, having defensible reasons for behaviours helps or protects people's self-confidence (Westaby, 2005), and guarantees a better feeling about themselves (Pieters & Zeelenberg, 2005). Reasons are foundations for understanding people behaviour such that several theories take reasons into account as the underlying determinants of behaviour. For instance, the theory of explanation-based decision making (Pennington & Hastie, 1993) asserts that people follow the logical reasons to evaluate and select alternatives in a rational decision-making process. Therefore, reasons play a crucial role in choosing an option by supporting its satisfactoriness and providing explanations for the alternative's suitability.

In the context of technological innovation adoption, according to the status quo base theory (Samuelson & Zeckhauser, 1988), users need justifiable reasons to overcome the psychological inertia (Snyder, 1992). Likewise, according to functional theorizing, any effort to trigger new behaviour would be successful only if it addresses the underlying reasons for that behaviour (Snyder, 1992; Westaby, 2005). Grounded on this theoretical lens, we consider users' reasoning as the central mechanism for understanding why users resist IoMT. Westaby (2005) refers to reasons as 'specific subjective factors people use to explain their anticipated behaviour', which have two broad sub-dimensions: 'reasons for' and 'reasons against' performing a behaviour (p. 100). The dichotomous view of reasons is aligned with dual-factor approaches in technology adoption studies (e.g., Cenfetelli & Schwarz, 2011; Lee et al., 2009; Park & Ryoo, 2013). Yet, *reasons for* and *reasons against* move beyond considering just the inherent duality of a phenomenon and provide explanation-based justifications for intended behaviour.

According to behavioural reasoning theory, reasons and beliefs are two different concepts (Westaby, 2005). Beliefs are subjective probability judgments about potential future outcomes of specific behaviours (Ajzen, 1991), whereas reasons specifically focus on the people's perceptions for explaining and justifying their behaviours (Westaby, 2005). For example, a user might strongly believe that using an IoMT device at work would generally result in enhanced efficiency, but they may choose not to use it because of strong *reasons against* (e.g., health data privacy concerns or intrinsic complexity). Thus, reasons are the dominant forces of the decision that can logically explain the personal rationalisation of their behaviours (Delgosha & Hajiheydari, 2020). In this study, we concentrate on the cognition process of users for making decisions about adopting or rejecting IoMT, which is a result of complex dynamics of their perception about '*reasons for*' and '*reasons against*' toward their ultimate decision.

We thus maintain that in the case of using IoMT in the healthcare industry, practitioners have reasons for their behaviour (here: resistance against using technology) that justify their decisions. If these reasons support their resistance behaviour, we consider them as reasons for, and when these factors logically challenge their resistance decisions, they are considered as reasons against.

2.3. **Scepticism and resistance toward using a technology**

Scepticism is a general belief that reflects users broad evaluation toward an innovation (Westaby, 2005), which portrays the 'users' doubtful approach toward innovations and the benefits that novel products offer (Jahanmir & Lages, 2016, p. 1702). In the innovation context, scepticism has been studied as a potential user cognitive response to new technological systems (Skarmeas & Leonidou, 2013). Skarmeas and Leonidou (2013) applied attribution theory to explain how consumers attribute their cognitive perception of contextual factors to their beliefs and behaviours. Further, according to Heider (1958), individuals consider both external (i.e., factors related to the new system) and internal (i.e., individual's personal characteristics) attributions to evaluate new situations to make a decision. In the service sector, Mani and Chouk (2018) found that scepticism is important for adopting innovative technologies like IoT, influencing the resistance of consumers toward using smart services.

Similarly, the resistance notion has long been acknowledged as a critical variable in technology adoption literature (Rivard & Lapointe, 2012). However, the nature of resistance is controversial in the literature, while some scholars interpret it as a barrier to be removed (e.g., Bhattacherjee, & Hikmet, 2007), others accept resistance as the nature of change that should be realised and understood (e.g., Cenfetelli & Schwarz, 2011). Either for examining the barriers of successfully diffusing an innovation, or for understanding the dynamism of user-innovation, using theories about resistance will lead to enhanced introduction strategies and, eventually, to improved innovation outcomes (Lapointe & Rivard, 2005). Based on the concept of 'resistance to change', user resistance to technology is an expected response to a change that is derived from an innovation (Ram & Sheth, 1989). From this angle, users incline to reject a newly introduced technology either because they are satisfied with the status quo (Mani & Chouk, 2018) or because the new system conflicts with their belief structure (Ram & Sheth, 1989).

User resistance, as an adverse reaction toward technological innovation, can negatively affect the initiative's destiny. Despite its organizational and individual promising effects, information technology initiatives generally fail as the result of users' resistance to adopting and using them (Cenfetelli & Schwarz, 2011). IoMT is not an exception, regardless of all aforementioned remarkable potentials. To understand the user reaction to technology, literature has mainly focused on examining users' cognitive processes to explain how the perception of technology benefits affects their behavioural 'positive decisions' (Claudy et al., 2015). As a result, we have witnessed well-developed grounds in technology adoption theories such as Technology Acceptance Model (TAM) (Davis, 1989), or Unified Theory of Acceptance and Use of Technology (UTAUT) (Venkatesh et al., 2003).

However, it is largely debated that adoption enablers are not simply the reverse of rejection antecedents (Cenfetelli & Schwarz, 2011; Delgosha & Hajiheydari, 2020). This view leads to the other stream of related research intending to understand the antecedents of customer resistance that explain why consumers incline to reject an innovation (e.g., Heidenreich & Kraemer, 2016; Kleijnen et al., 2009). In this regard, Ram and Sheth (1989) categorize inhibitors as the anti-adoption or resistance main drivers into functional and psychological barriers of using emergent technologies. However, more recently Mani & Chouk (2018) extend this classification by adding individual barriers. Further, various key antecedents are broadly discussed in the literature as technology inhibitors such as 'usage barriers' (Laukkanen et al., 2007), 'value barriers' (Lian & Yen, 2014), 'risk barriers' (Herzenstein et al., 2007), 'image barriers' (Antioco & Kleijnen, 2010), 'tradition barriers' (Ram & Sheth, 1989), and 'technology anxiety barriers' (Evanschitzky et al., 2015). These factors hinder the likelihood of adopting new technologies through different justification mechanisms. In this study, to better understand the resistance behaviour, we conceptualise it as a complex phenomenon since clusters of interconnected drivers shape and influence users' resistance (El Sawy et al., 2010; Mani & Chouk, 2018).

2.4. Reasons for IoMT scepticism and resistance

To extract and empirically test the factors that are salient to IoMT users' behaviour, in this study, we categorised reasons for and reason against scepticism and resistance into three clusters of System, Information and Individual related factors. We thus referred to the extant literature of resistance/acceptance and selected the factors that are theoretically relevant to using IoMT.

2.4.1. System-related reasons

Perceived security risk: refers to concerns about the possibility of losing control over private and personal data (Kleijnen et al., 2007). Perceived security risk makes users concerned about data breaches. Users' uncertainty about the probability of fraudulent behaviour by the technology provider organization (Miyazaki and Fernandez, 2001) or cybercriminals because of technological vulnerability (Kim et al., 2010) hinders adopting technology, especially in the context of healthcare. Many studies stress the potentiality and negative consequences of data and information abuse in the context of information technology (e.g., Chellappa, 2008; Hartono et al., 2014) and more specifically in using smart devices (e.g., Bastos et al., 2018; Klobas et al., 2019; Park & Shin, 2017). A recent report published by IBM also highlighted the increasing vulnerability of hospitals in the face of cybercriminals as a result of the IoMT proliferation, along with insufficient access controls, unpartitioned networks, and legacy systems (Security Intelligence, 2019), which can be a matter of life and death in the health sector.

Perceived complexity: Perceived complexity, which refers to the 'degree to which an innovation is perceived as difficult to understand and use' (Rogers, 2003, p. 242), emerges from two different but related sources. First, users evaluate the complexity degree of the innovation idea (its understandability) and second, they assess its execution complexity (its usability) (Ram, 1987). Qureshi & Krishnan (2018) contend that one of the influential reasons that kept the IoMT adoption rate lower than smart home devices or smart tracking technologies is its overly complicated perception. Several studies point out that perceived complexity impedes innovation diffusion in different contexts like ERP implementation (e.g., Bradford & Florin, 2003), mobile banking (e.g., Al-Jabri & Sohail, 2012; Cheng et al., 2014), e-commerce (Hansen, 2005; Verhoef & Langerak, 2001), and IoT applications (Lin et al., 2016). Similarly, in the context of IoMT, if users deem these technological devices too complex to understand and use, they prefer to avoid them.

Effort redundancy: is defined as the system's requirements for 'unnecessary repetition of already performed steps such as' entering in name and address twice or losing already stored information' (Cenfetelli & Schwarz, 2011 p. 815). If a system necessitates repetitions of some previously completed activities, users feel hassled and will more likely reject the system. Cenfetelli and Schwarz (2011) argue that being forced to repeat some steps in using a new technological system is a usage inhibitor. Not surprisingly, IoMT, similar to other health-related technologies, include prospectively monitored redundancies to decrease the risk of human or system errors (Ash et al., 2004; McGinnis et al., 2011).

Process uncertainty: Difficulty to understand whether a system has correctly and thoroughly processed the user request is defined as the process uncertainty (Cenfetelli & Schwarz, 2011). When users want to use a new system, they expect more process clarity (Davis, 1982), and if they perceive ambiguity and uncertainty regarding the new system process, their adoption intention declines. By using the innovative systems, users assume higher levels of structuredness, analysability and routines (Gebauer & Schober, 2006) that result in transparency and predictability. In a complex technological context, like IoMT, users' understanding of the procedures and the certainty about the results might be blurred, which in turn, leads to increased hesitation in applying the technology.

2.4.2. *Information-related reasons*

Information overload: If the amount of information goes beyond the user's needs or process capacity (Zhang et al., 2018), it results in perceptions of being overwhelmed (Liang et al., 2006). Information overload is counterproductive; it negatively influences the user's performance and decision-making, as it overburdens her cognitive limitations (Lurie, 2004). Consequently, the user needs to remove irrelevant or redundant information (Xu et al., 2014) to understand the situation and make a decision. Researchers posit that information overload negatively influences users' satisfaction (Liang et al., 2006), and inhibits using new technology (Zhang et al., 2018). In the healthcare context, making decisions under time limitation becomes more vital, and feeling overwhelmed with loads of redundant or irrelevant information makes the situation complicated for the practitioners.

Deceptiveness: Providing inaccurate or incorrect information leads to the perception of the system's inability to meet the expectations or promises (Cenfetelli & Schwarz, 2011). If users find the IoMT information misleading or manipulative, credibility, accuracy, and objectivity of the system (Wang & Benbasat, 2016) will be tarnished in their eyes, and they become sceptical toward it. Recognition of deceptiveness in IoMT systems not only stimulates usage rejection, but it is also more likely to jeopardize the other perceived positive aspects of systems (Cenfetelli & Schwarz, 2011).

2.4.3. Individual-related reasons

Inertia: The influential role of inertia on user resistance to new systems has been discussed in several studies (e.g., Li et al., 2016; Polites & Karahanna, 2012; Tsai et al., 2019). When a user's frequently performed behaviour becomes habitual, she tends to continue it automatically over time (Limayem et al., 2007). According to the status quo bias (SQB) theory (Samuelson & Zeckhauser, 1988), humans become biased toward maintaining the status quo. SQB ultimately manifests itself externally as inertia. Inertia is defined as 'attachment to, and persistence of, existing behavioural patterns (i.e., the status quo), even if there are better alternatives or incentives to change' (Polites & Karahanna, 2012, p. 24). With greater inertia, it is more likely that users persist in continuing the current status either because this is what they have always done before or it may be too stressful to change. Hence, if users find IoMT incompatible with their deeply ingrained routine behaviours, they resist it.

Psychological reactance: Similar to habit, another psychological dimension i.e., reactance provides some explanation for resisting an innovation. Psychological reactance refers to the tendency to negatively react to liberty or freedom deprivation or elimination (Clee & Wicklund, 1980). This reaction is explained by the user's motivational state when she feels that her freedom is threatened (Clee & Wicklund, 1980). Banikema and Roux (2014) proved that psychological reactance positively relates to users' scepticism. Psychologically, and in line with 'reactance theory' (Brehm 1966), the sense of being controlled by technology or feeling that their freedom is limited as a result of being tied to IoMT devices can establish a reason for rejecting technology.

2.5.Reasons against IoMT scepticism and resistance

2.5.1. System-related reasons

Compatibility: The importance of users' beliefs about the practical or normative technology compatibility (Tornatzky & Klein, 1982) as an antecedent of technology adoption is widely discussed. Perceived compatibility is defined as the degree to which a technology is believed to be consistent with the user values, needs, and experiences (Rogers, 2003). Compatibility is discussed to be more significant in the process of technology adoption configuration as it is conceptualized with positive causal linkages to perceived ease of use and usefulness (Karahanna et al., 2006). Thus, when users find smart healthcare devices well-matched with their current work practice and experience, it is less likely to resist using them for their daily work purposes.

Convenience: Saving time and effort is an original motive for using modern technology. Originated in marketing and consumer behaviour (Berry et al., 2002), the notion of convenience is considered as an influential factor in technology adoption (e.g., Chan et al., 2010; Hajiheydari & Ashkani, 2018; Lai, 2017). Facilitating the accomplishment of planned tasks and making them more appealing are the results of user understanding about how convenient technology is (Teo et al., 2015). Thus, users with the perception of greater convenience in using technology would consider it as 'useful' and 'easy to use' (Childers et al., 2001). Similarly, in the context of smart health, if IoMT proposes convenient working methods, health practitioners will more likely adopt it.

Reliability: Stemmed in reliability engineering, Zahedi (1987) defines system reliability as 'the probability that the system remains successful (does not fail) in achieving its intended objectives within a given period of time and under a given set of conditions' (p. 188). Therefore, reliability is a core characteristic for understanding the system dependability over time, and is discussed to have a positive impact on health information technology adoption (Everson et al., 2014). Although reliability is objectively measurable by some empirical metrics (Nelson et al., 2005), users can have their own perceptions about the reliability of a system based on personal experience and expectations. While users in hospitals work under emergency conditions, they expect higher levels of reliability from the system performance. Reliability briefly reflects the most influential determinant of system quality as it guarantees the promised service dependably and accurately (Jiang et al., 2000).

Flexibility: If users find the system capable of adapting to a wide variety of needs or responding to a changing condition (Nelson et al., 2005), they feel more confident in using it. Flexibility, also interpreted as maintainability and adaptability of the system for responding to changing needs, is considered as a feature of quality from users' viewpoint in literature (Gorla et al., 2010). In the vibrant healthcare context, which is less planned and more dynamic, the flexibility feature for IoMT systems looks quite appealing.

2.5.2. *Information-related reasons*

Information Accuracy: Information accuracy as the intrinsic dimension of information quality (Wang & Strong, 1996) stands for accessing accurate and consistent information (Levitin & Redman, 1998). Accuracy is mainly explained as the correctness of the provided information in mapping with the real-world state (Fisher & Kingma, 2001), and is considered as the basic expectation of the user from an information system (IS). Scholars maintain that information accuracy determines users' tendency to adopt a system (Hajiheydari & Ashkani, 2018; Kuo & Lee, 2009; Zheng et al., 2013). If users generally sense that the provided information by IoMT supports its believability, correctness, and consistency with their experience, the more likely they show intention toward applying it.

Information Currency: Beyond accuracy, users expect to receive up-to-date information, which reflects the *current state* of the world. Currency is identified as a contextual factor of information quality (Nelson et al., 2005), which represents the users' understanding about providing the most recent information by the system (Cappiello, et al., 2003). Users thus more willingly adopt work-related technologies that provide up-to-date information (Brown et al.,

2010). In dynamic environments such as healthcare context, the importance of receiving up-to-to-date information from systems increases.
Information Completeness: Users expect to get complete information about the most recent state of the situation. Information completeness is another contextual dimension of information quality (Nelson et al., 2005), and is defined as the user perception about the sufficiency of breadth, depth, and scope of available information (Wang & Strong, 1996). Perceiving the information as comprehensive and exhaustive, representing the main aspects of the interested subject (Filieri & McLeay, 2014) facilitates users' task performance and decision-making process, and thus is proposed as an influential dimension of health information system quality (Yusof et al., 2008). While the patient record completeness is not easily guaranteed by the current healthcare information systems (Nasir et al., 2016), IoMT provides the infrastructure for sensing and collecting health data from the sources (e.g., patients' vital signs).

2.5.3. *Individual-related reasons*

Perceived enjoyment: Apart from the expected performance**,** using technology could be perceived as enjoyable (Davis et al. 1992), based on its capabilities in providing self-fulfilling. The hedonic aspect of using innovation besides leisure activities encourage prolonged use of a system (Van der Heijden, 2004). Regardless of its functional capabilities, when users find a technological innovation (here IoMT) as fun, enjoyable and pleasant, their resistance will decrease.

Need for Uniqueness: Users' need for feeling differentiated from other people (Tian et al., 2001) can be a stimulus for using an innovative technology that enhances self-perceptions of differentness (Hang & Tam, 2006). Thus, we argue that healthcare practitioners might be motivated to acquire and use IoMT devices with the purpose of developing and enhancing their distinctive personal and social image.

Self-efficacy: When users feel self-confident, and they believe in their abilities in using a system competently, they feel less anxiety (emotional response) (Bandura, 1982) and show higher performance (individual reaction) (Barling & Beattie, 1983). The significant influence of self-efficacy on individuals' expected outcomes of using new technology is broadly discussed (Compeau & Higgins, 1995; Hajiheydari & Ashkani, 2018). Similarly, in the hospital context, users with higher self-efficacy show more behavioural intention to use contemporary information technologies in performing their tasks (Aggelidis & Chatzoglou, 2009). Hence, when users find themselves capable of applying IoMT devices, it is less likely to stand against its application.

2.6. The research theoretical model

Given the above theoretical reasoning, we develop a conceptual model that is illustrated in Figure 1. A series of reasons for and reasons against at three categories of system, information and individual is proposed as predictors of scepticism and resistance towards using IoMT. As shown in the model, scepticism stimulates IoMT resistance. We will test the proposed model using two analytical approaches, namely PLS-SEM and fsQCA, to gain deeper insights into complex interactions of factors that predict behaviours of IoMT users. PLS-SEM investigates path analyses of reasons for and against scepticism and resistance toward using IoMT, while fsQCA explores configurations (i.e., a combination of the factors) to predict a given outcome (e.g., resistance to using IoMT) (Olya & Al-Ansi, 2018).

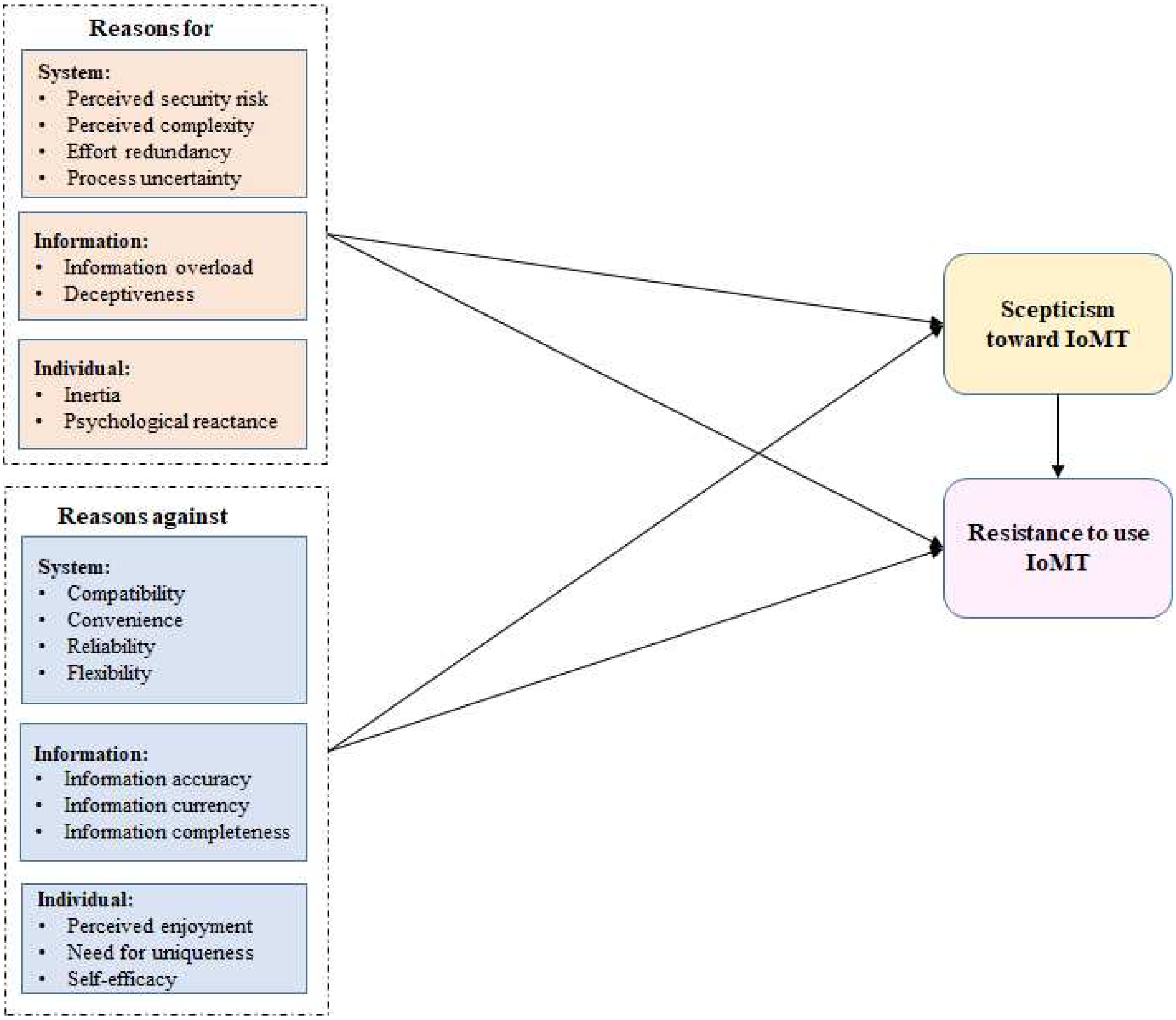

Figure 1. Research theoretical model

3. Research design and methodology

3.1. Instrument development

To develop the survey instrument, we have used validated scales from previous research and adapted them to fit the context of IoMT. Perceived security risk was measured with three items adapted from Mani and Chouk (2018). We adapted the three items for measuring perceived complexity from Moore and Benbasat (1991). Three items for measuring effort redundancy and three items for measuring process uncertainty adapted from Cenfetelli and Schwarz (2011). We adapted the items for measuring information overload and deceptiveness from Zhang et al. (2018). Inertia was measured with three items adapted from Mani and Chouk (2018). Psychological reactance was measured with three items from the scale proposed by Banikema and Roux (2014). We adapted the three items for measuring perceived compatibility from Karahanna et al. (2006). To measure convenience, a scale of three items was used from Claudy et al. (2015). Reliability was measured with three items adapted from Zahedi (1987). We adapted three items for measuring information currency from Xu et al. (2014). Three items for measuring flexibility adapted from Gorla et al. (2010). Information accuracy was measured with three items from Arbore et al. (2014). We adapted the three items for measuring information completeness from Nelson et al. (2005). Perceived enjoyment was measured with three items adapted from Van der Heijden (2004). Four items for measuring the need for uniqueness were adapted from Hong et al. (2006). To measure self-efficacy, three items were adapted from Compeau & Higgins (1995). Regarding scepticism, the scale of Banikema and Roux (2014) was adapted. Finally, we adopted five items for measuring resistance from Wiedmann et al. (2011). All of the survey items were measured using a seven-point Likert scale anchored from 'strongly disagree' (=1) to 'strongly agree' (=7). Appendix 1 lists the questionnaire items used to measure each construct, along with descriptive statistics and loadings.

We validated our instrument in three steps. First, three academic experts reviewed the survey instrument along with definitions of constructs. Second, to validate face and content validity, we conducted a sorting exercise with three researchers. The three judges correctly placed the items onto the intended constructs. The results of sorting showed that Cohen's Kappa scores averaged 0.84, the interjudge raw agreement scores averaged 0.82, and the average overall placement ratio of items within the targeted constructs was 0.86. Third, we further validated our instrument through a pilot study, involving 30 participants to ensure that the mechanics of compiling the questionnaire had been adequate. The pilot study helped us assess the time to complete the questionnaire, ease of understanding, logical consistency, terminology, and the suitability of the format. The comments collected based on open-ended inputs from the participants led to minor wording changes. Reliability assessment in the pilot studies indicated all constructs were reliable. In addition, the factor analysis confirmed convergent and discriminant validity. The results of the pilot study showed that the survey instrument was appropriate for use in a larger study.

3.2.Research context and data collection

In order to investigate the ground reasons that justify users' resistance toward using IoMT, this study draws on data collected from healthcare practitioners through a 4-months survey from September to October 2019 in a developing country, Iran. Recently, according to the 'Health Sector Transformation Plan' developed by the Iranian Ministry of Health and Medical Education, hospitals in Iran are experiencing dramatic technological changes, especially for health monitoring innovations (Mahdavi et al., 2018). For instance, developing telehealth systems is recognised amongst the top 5 priorities for technology advantments in the health sector vision plan (Dehghani et al., 2017). Furthermore, recently 'chronic disease management' and 'patient surveillance' have been top IoT applications in Iranian hospitals (Ghasemi et al., 2016). We collected our data via an on-site survey in five hospitals in Tehran, Iran. One of the main selection criteria was that selected hospitals intended to employ IoMT in their operations in the near future so that their staff were qualified to respond to survey measures. We negotiated with managerial teams of selected hospitals while sending a letter of permission for data collection. We also ensured that the survey was approved by their institutional ethical committee. After the official steps, paper-based questionnaires were distributed among staff. The purpose of our study was explained in the questionnaires and participants were informed that their responses would remain anonymous and confidential to minimise potential common method bias (Podsakoff et al., 2003). Out of 750 distributed questionnaires, 481 were returned, from which, 427 appropriately completed answers were finally analysed. The demographic specification of this survey sample is presented in Table 1.

As IoMT is still in its infancy and many health practitioners have not directly experienced them, participants were provided with a short description to establish a common understanding of technology among all respondents. After reading the instructions on IoMT, hospital staff answered questions regarding both *reasons for* and *reasons against* resistance to using the technology.

Table 1. Descriptive statistics of respondents

Age	***n***	**%**
Under 25	35	8%
25-35	143	33%
35-45	167	39%
45-55	65	15%
More than 55	17	4%
Gender	***n***	**%**
Female	241	56%
Male	186	44%
Education	***n***	**%**
Undergraduate degree	235	55%
Postgraduate degree	105	25%
Doctorate degree	87	20%
Experience of working in healthcare	in Month	
	Mean= 30.36	SD= 9.72
Income	in US$	
	Mean= 30.400	SD= 18.500

4. Data Analysis and Results

We analysed our data and research model in three steps using SPSS 23.0, SmartPLS 3.2.8 and fsQCA 3.0 software. In the first step, we used confirmatory factor analysis (CFA) to test the quality of measuring our constructs. In the second step, we applied partial least squares (PLS) as a well-suited symmetrical analysis method to evaluate the net effects of predictors on the outcomes of interest. PLS is a preferred modelling technique for testing various relationships between multiple independent and dependent variables simultaneously (Lowry & Gaskin, 2014) and when researchers intend 'to study associations between latent variables when new theoretical ground is being explored' (Ray et al., 2012, p. 205). In the third step, this study employed fsQCA to examine asymmetrical, combinatorial effects of condition variables on the outcomes. By using the fsQCA technique, we attempted to identify sufficient relations that explain the intended outcomes.

4.1.Psychometric quality of constructs

To check our measurement model, we conducted confirmatory factor analysis through convergent and discriminant validity tests. As per Kim et al. (2018), convergent validity can be established by examining reliability, the standardised path loading, and the average variance extracted (AVE) of the constructs. To check the construct reliability, we used Cronbach's alphas and composite reliabilities and all the values were higher than the accepted threshold of 0.70 (see Appendix 1). As presented in Appendix 1, the standardised path loadings were all significant and greater than 0.7. The average variance extracted (AVE) for each construct exceeded 0.50 (the recommended level), meaning that more than one-half of the variance observed in the items was explained by their latent constructs (Venkatesh et al., 2016). The discriminant validity of constructs was established by the Fornell-Larcker (1981) test which ensures variance that each latent construct shares with its indicator is greater than the variance it shares with the other constructs. To this aim, we examined discriminant validity by comparing the square root of AVEs with the correlations between constructs.

We further tested the presence of common method variance (CMV) in our data by using Harman's single-factor test (Podsakoff et al., 2003). In this test, we check the existence of CMV, if a single factor emerges from the factor analysis or one general factor accounts for the majority of the covariance in the independent and dependent variables (Podsakoff et al., 2003). For our sample, unrotated factor analysis indicated that the first factor accounted for 37% of the total variance. The principal component analysis with oblique rotation showed that each emergent factor explained an almost equal amount of the total variance, ranging from 9.23% to 13.21%. As a result, common method bias was not a major concern in this study.

4.2.Net effects analysis with PLS-SEM

To analyse the net effects and symmetrical relationships, we used SmartPLS 3.2.8 for bootstrapping resampling technique with 427 cases and 5,000 randomly generated (Hair et al., 2016). PLS-SEM uses two measures to assess the net effects and predictive power of a model: coefficient of determination (R^2) as an indicator of predictive accuracy, and Stone–Geisser's Q^2 as an indicator of predictive relevance (Hair et al., 2016). PLS-SEM also assesses the size and significance of the path coefficients. Results indicated that the proposed model explained 44.1% of the variance (R^2) in scepticism towards IoMT, and 51.2% of the variance in resistance to using IoMT. Using blindfolding, Q^2 was 0.311 for scepticism and 0.329 for resistance. All values were greater than the accepted threshold of zero (Hair et al., 2016).

The net effects analysis results are presented in Table 2. According to PLS results, among the *reasons for*, all system-related factors (i.e., perceived security risk, perceived complexity, effort redundancy, and process uncertainty), deceptiveness as an information factor, and inertia as an individual factor have significant positive effects on scepticism and resistance towards using IoMT. Among the *reasons against* compatibility, convenience, and reliability as system-related factors, information accuracy, currency, and completeness as information related factors, and need for uniqueness as an individual related factor significantly and negatively affects scepticism. Likewise, all of these *reasons against* conditions except information currency positively affect resistance. Furthermore, scepticism was found as a significant positive predictor of resistance.

Additionally, since Mani and Chouk (2018) considered the mediating effect of scepticism in their proposed model, we tested whether the effects of reason on resistance towards IoMT are mediated by scepticism. We found that scepticism mediates most of the positive relationships between *reasons for* and resistance and some of the negative relationships between *reasons against* and resistance (please see Appendix 2).

Table 2. *The results of net effect analysis*

Reasons	Level	Predictors	Outcome	
			Scepticism	Resistance
For	System	Perceived security risk	0.34**	0.28**
		Perceived complexity	0.39**	0.41**
		Effort redundancy	0.27**	0.18*
		Process uncertainty	0.19*	0.14*
	Information	Information overload	0.09	0.06
		Deceptiveness	0.32**	0.44**
	Individual	Inertia	0.12*	0.21**
		Psychological reactance	0.05	0.09
Against	System	Compatibility	-0.21**	-0.25**
		Convenience	-0.26**	-0.33**
		Reliability	-0.18*	-0.14**
		Flexibility	-0.03	-0.05
	Information	Information accuracy	-0.23**	-0.23**
		Information currency	-0.13*	-0.10
		Information completeness	-0.15*	-0.19*
	Individual	Perceived enjoyment	-0.04	0.02
		Need for uniqueness	-0.11*	-0.11**
		Self-efficacy	-0.05	-0.08
		Scepticism		0.31**
R^2			0.44	0.51
Q^2			0.31	0.33

Note: *p<.05; **p<.01; ***p<.001

4.3. Configurational analysis with fsQCA

Using a configurational theory approach and fuzzy-set qualitative comparative analysis, this study explores how *reasons for* and *reasons against* combinatorial impacts shape resistance outcome toward IoMT usage. fsQCA is a set-theoretic method that empirically explores the relationships between the outcome and all possible causal combinations of theoretically relevant predictors. This technique assists researchers to go beyond conventional regression-based methods (CRBM), by providing the opportunity to identify multiple causal configurations explaining the same outcome (Delgosha et al., 2020; Pappas, 2018). fsQCA explicates the nonlinear and emergent links between the causal combination of the antecedents and outcome of interest in terms of conjunctural, equifinal, and asymmetric elements (Schneider & Wagemann, 2012; Olya & Han, 2020). Conjunction implies that outcomes mostly emerge by combinations of multiple conditions, rather than a single cause. Equifinality points out that there is more than a single path leading to the outcome (Misangyi et al., 2017). Asymmetry means that ‘the causes for occurrence of an outcome are not necessarily the inverse of the causes of its absence and therefore each requires separate theoretical and empirical consideration; it also implies that the presence versus absence of attributes may play different roles in the occurrence of outcome’ (Greckhamer, 2016, p. 799).

fsQCA helps researchers to identify necessary or sufficient subset relations (Ragin, 2008). Attributes may be considered necessary if they must be present for an outcome to occur, and sufficient if they can produce an outcome by themselves. The fsQCA procedure starts with calibrating the data. Through the calibration process based upon empirical and/or theoretical knowledge, membership scores are determined and assigned to the cases in the outcomes and causal conditions sets (Greckhamer, 2016). We used direct method calibration to convert seven-point Likert scales, such that non-full membership was assigned to 2, crossover-point was assigned to 4, and full membership was assigned to 6 (Delgosha et al., 2020; Wang et al., 2018; Olya & Han, 2020).

In the next step, calibrated sets are examined via fsQCA truth table for identifying configurations resulting in the outcome. In the fsQCA process, a truth table of 2^k rows is built, with k representing the number of conditions, and each row representing a logically possible configuration of condition variables. Further, the truth table is refined based on two criteria of consistency and frequency (Ragin, 2008). Consistency refers to 'how reliably a combination results in the outcome, a measure that is similar to the significance level in regression analysis' (Park & Mithas, 2020, p. 92). We set 0.8 for consistency as the minimum acceptable threshold, following the recommendation of Rihoux and Ragin (2009). Frequency represents the number of cases for each possible combination. To ensuring that a minimum number of observations exists for the assessment of relationships, a frequency cut-off point needs to be set. For samples in more than 150 cases, the frequency threshold has been proposed to be three (Delgosha et al., 2020; Fiss, 2011; Rihoux & Ragin, 2009). Considering our sample size, 427 participants, we set the minimum acceptable number of cases in each configuration to three, thus all combinations with smaller frequencies are removed from the table.

The truth table produces three kinds of solutions (complex, intermediate, and parsimonious) based on counterfactual analysis, i.e. examining configurations that do not exist in the sample data. fsQCA uses counterfactual analysis to make some simplifying assumptions and minimise the number of elements in the truth table configurations in order to explore more concise configurations that lead to the outcome. In this study, we leverage parsimonious and intermediate solutions (Greckhamer, 2016; Ragin, 2008). Parsimonious solutions are generated by applying all simplifying assumptions (Olya, 2020) and yield the most important conditions. For producing intermediate solutions, researchers use simplifying assumptions consistent with empirical evidence and their theoretical knowledge (Greckhamer, 2016; Rihoux & Ragin 2009).

In this study, to develop intermediate solutions, we applied the following counterfactuals based on prior knowledge. We integrated the presence of *reasons for* conditions (i.e., perceived security risk, perceived complexity, effort redundancy, process uncertainty, information overload, deceptiveness, habit, and psychological reactance) and the absence of *reasons against* conditions (i.e., compatibility, convenience, reliability, flexibility, information accuracy, information currency, information completeness, perceived enjoyment, need for uniqueness, and self-efficacy) for high scepticism and resistance towards using IoMT. Inversely, we integrated the absence of system, information, and individual *reasons for* conditions and presence of system, information, and individual reasons *against conditions* as easy counterfactuals for low scepticism and resistance. We also included the presence of scepticism as an easy counterfactual for high resistance.

Figures 2 and 3 show fsQCA configurational analysis results for high and low scepticism and resistance to using IoMT. In presenting configurations, we used the notation proposed by Fiss (2011) and differentiated between core conditions that have strong causal links to the outcome (part of both parsimonious and intermediate solutions), and complementary conditions with a weaker causal relationship to the outcome (only part of intermediate solutions). We also reported overall consistency and coverage measures besides each configuration's consistency, raw and unique coverage scores (Ragin, 2008). Consistency scores of all configurations are above the recommended threshold (>0.8), which indicates that configuration solutions are consistently led to the outcome (Wang et al., 2019). The overall solution coverage reveals the extent to which the outcome of interest explained by identified configurations, an indicator similar to R^2 reported in regression analysis (Pappas et al., 2019). An overall solution coverage of 0.56 to 0.78 shows that the extracted configurations are able to capture a significant percentage of the membership of the outcome set (Wang et al., 2019). In addition, by measuring the raw and unique coverage, fsQCA evaluates the empirical relevance of each configuration. The raw coverage computes the proportion of the outcome that is explained by a specific configuration. The unique coverage reports how much of the outcome is explained exclusively by a specific configuration. As shown in Figures 2 and 3, identified configurations explain a substantial variation of outcomes (scepticism and resistance), ranging from 19% to 69% of cases.

Four configurations were consistently linked to low scepticism towards using IoMT (Figure 2). Configurations for low scepticism are represented by 'L' and configurations for high scepticism are represented by 'H'. Low score for scepticism is the negation of the scepticism factor. Among these configurations, L1 has the greatest raw/unique coverage score which means that empirically it is the most relevant solution for explaining low scepticism towards using IoMT. Low unique coverage of the other three configurations (from 0.01 to 0.04) implies high overlap among these solutions (L2-4) and L1. As a result, L1 is the most significant configuration for predicting low scepticism and the other configurations are adjusted or modified versions of L1. The necessity analysis for a low level of scepticism illustrates that among *reasons for* conditions, information accuracy and among *reasons against* factors, perceived complexity are core conditions for realizing this outcome. While, results show that L1 and L4 are two separate configurations, meticulously examining their structure indicates that they are identical in terms of the presence and absence of conditions, but different regarding the power degree of conditions (core and complementary). Put differently, healthcare practitioners with the same set of *reasons for* and *reasons against,* have a low level of scepticism toward using IoMT, yet they might have different stress on perceived security risk, effort redundancy, deceptiveness, reliability, and information currency. In comparison with L1, perceived security risk, inertia, reliability, flexibility, and perceived enjoyment are "don't care" attributes in L2. Also, in L3 configuration compared to L1, process uncertainty and flexibility are irrelevant conditions.

Results reported in figure 2 present four configurations leading to high scepticism towards using IoMT. Sensibly examining necessary and sufficient conditions for scepticism reveal three important points. First, the necessary condition and configurational analysis indicate that the absence of convenience and information accuracy are essential, core conditions for occurring scepticism, while other attributes are complementary and have relatively weaker causal relationships with the scepticism. Second, H1 by some means is the opposite of L1 configuration for low scepticism. In H1 configuration, perceived enjoyment is a 'don't care' condition, wherein L1, information overload and psychological reactance are irrelevant conditions. Similar to L1 configuration, H1 has the largest raw coverage among the configurations leading to high scepticism, thus it is a substantial solution for this outcome. Third, in comparison to H1, the presence of perceived security risk, effort redundancy (S4), physiological reactance (S2), and information overload (S2-4), and also the absence of compatibility (S3), convenience (S2), flexibility (S2-3), self-efficacy (S3), and need for uniqueness (S2-4) are 'don't care' conditions.

Configuration condition			Configurations for Low Scepticism				Configurations for high Scepticism			
			L1	L2	L3	L4	H1	H2	H3	H4
Reasons for	System	Perceived security risk	⊗		⊗	⨂	●	•	•	
		Perceived complexity	⨂	⨂	⨂	⨂	●	•	•	●
		Effort redundancy	⨂	⊗	⨂	⊗	•	•	•	
		Process uncertainty	⨂	⊗		⨂	•	●	●	•
	Information	Information overload					•			
		Deceptiveness	⨂	⊗	⊗	⊗	●	•	●	•
	Individual	Habit	⊗		⊗		•	•		•
		Psychological reactance			⊗		•		•	•
Reasons against	System	Compatibility	•	●	•	●	⨂	⊗		⨂
		Convenience	●	●	•	•	⨂	⨂	⨂	⨂
		Reliability	•		•	•	⊗		⊗	⊗
		Flexibility	•			•	⊗			⊗
	Information	Information accuracy	●	●	●	●	⨂	⨂	⨂	⨂
		Information currency	•	•	•	•	⊗			⊗
		Information completeness	●	•	•	•	⊗	⊗		⊗
	Individual	Perceived enjoyment	•							
		Need for uniqueness	●	•	•	●	⊗			
		Self-efficacy	•	•		•	⊗	⊗		⊗
Consistency			0.94	0.83	0.87	0.91	0.9	0.89	0.81	0.95
Raw Coverage			0.67	0.21	0.27	0.31	0.58	0.33	0.19	0.26
Unique Coverage			0.23	0.01	0.02	0.04	0.26	0.05	0.01	0.02
Overall solution consistency			0.85				0.93			
Overall solution coverage			0.56				0.73			

Note: Black circles (•) indicate the presence of a causal condition, and (⊗) circles represent the absence of a causal condition; big circles = core conditions; small circles = complementary conditions; Blank spaces indicate 'don't care'.

Figure 2. Configurations for high and low scepticism

As depicted in Figure 3, eight configurations consistently lead to resistance to using IoMT, among which five paths link to high resistance and three paths proceed to low resistance. Necessity analysis shows that perceived complexity and lack of convenience are essential causes in configurations for high resistance with consistency scores of 0.91, 0.93 respectively. Findings demonstrate that these two conditions coupled with the presence of process uncertainty (H2), deceptiveness (H3), and scepticism (H1, H3, H5), as well as lack of compatibility (H5), and information accuracy (H3-5) establish salient core conditions for high resistance to using IoMT. Greater raw/unique coverage of H1 configuration indicates that the high perceived complexity and scepticism with a lack of convenience are empirically more effective causes in occurring resistance behaviour. In H1 path, system reasons (both for and against) and information *reasons against* conditions are more relevant to the resistance outcome. Deceptiveness, inertia, and lack of self-efficacy are also the other complementary conditions in this configuration. H2 causal recipe is almost the modified version of H1, wherein effort redundancy, deceptiveness, lack of reliability, information currency and self-efficacy do not matter, thus H1 and H2 might have a substituting effect. H3 has the same structure as H1 in terms of presence and absence of conditions. In H3 path, perceived security risk, deceptiveness, and lack of information accuracy are core elements, wherein H1 they play the peripheral role condition. Investigating H4 configuration underscores that cases in this group are more sensitive to individual elements. Both *reasons for* and *against* individual conditions such as inertia, psychological reactance, lack of enjoyment, need for uniqueness, and self-efficacy are important elements for generating resistance in this group. By examining H5 configuration, it reveals that information factors (presence of information overload and psychological reactance, and lack of information accuracy, currency, and completeness) are relevant conditions that result in resistance using IoMT. Even perceived security is a core condition in H5, which means that issues concerning informational attributes are salient in this path.

For low resistance to IoMT, fsQCA pinpoints three configurations leading to the outcome. Empirically, L1 is relatively a dominant path to low resistance as it has larger raw/unique coverage (0.69/0.27). This configuration holds a combination of deceptiveness and lack of information accuracy as core conditions, besides all the other conditions as complementary elements (except information overload, psychological reactance, flexibility, and self-efficacy as 'don't care' conditions). In L2 causal path, lack of perceived complexity and convenience as core conditions combined with lack of perceived security risk, psychological reactance, and scepticism, as well as the presence of compatibility, flexibility, information accuracy, currency, and completeness, and self-efficacy as peripheral conditions to result in low resistance. The structure of L3 configuration is identical to L1, except that information completeness is irrelevant in L3. In addition, lack of perceived security risk, perceived complexity, and process uncertainty, along with high compatibility are salient conditions for the outcome.

Configuration condition			L1	L2	L3	H1	H2	H3	H4	H5
			Configurations for low Resistance			Configurations for high Resistance				
Reasons for	System	Perceived security risk	⊗	⊗	⨂	•	•	●		●
		Perceived complexity	⊗	⨂	⨂	●	●	●	●	●
		Effort redundancy	⊗		⊗	•		•	•	
		Process uncertainty	⊗		⨂	•	●	•		•
	Information	Information overload								•
		Deceptiveness	⨂		⊗	•		●	•	•
	Individual	Habit	⊗		⊗	•	•		•	
		Psychological reactance		⊗					•	•
Reasons against	System	Compatibility	•	•	●	⊗	⊗		⊗	⊗
		Convenience	•	●	•	⨂	⨂	⨂	⨂	⨂
		Reliability	•			⊗		⊗		
		Flexibility		•					⊗	
	Information	Information accuracy	●	•	•	⊗	⊗	⨂	⨂	⨂
		Information currency	•	•	•	⊗		⊗		⊗
		Information completeness	•	•		⊗	⊗	⊗		⊗
	Individual	Perceived enjoyment	•						⊗	
		Need for uniqueness	•		•				⊗	
		Self-efficacy		•		⊗		⊗	⊗	
Scepticism			⊗	⊗	⊗	●	•	●	•	●
Consistency			0.95	0.89	0.93	0.91	0.94	0.82	0.86	0.95
Raw Coverage			0.69	0.45	0.33	0.54	0.37	0.24	0.23	0.29
Unique Coverage			0.27	0.04	0.02	0.11	0.04	0.01	0.01	0.02
Overall solution consistency			0.92			0.87				
Overall solution coverage			0.78			0.61				

Note: Black circles (•) indicate the presence of a causal condition, and (⊗) circles represent the absence of a causal condition; big circles = core conditions; small circles = complementary conditions; Blank spaces indicate 'don't care'.

Figure 3. Configurations for high and low resistance

5. Discussion and Implications

5.1. Discussion

This empirical study uses behavioural reasoning theory to provide a holistic view of healthcare practitioners' behaviours toward IoMT by applying a multi-analytical approach including symmetrical (net effect) and configurational analysis. The results of our study offer several key findings on distinct and configurational impacts of reasons that predict scepticism and resistance towards using IoMT in healthcare services. A notable finding from net effects analysis is that among *reasons for,* deceptiveness, perceived complexity, and perceived security risk have the strongest net effects on scepticism and resistance.

These findings are in line with prior work on adopting/resistance towards smart devices. For instance, similar to other studies (e.g., Bastos et al., 2018; Klobas et al., 2019; Park & Shin, 2017), we notice that healthcare practitioners have concerns about security issues and are worried about the increasing likelihood of data breaches due to using IoMT (Kim & Kwon, 2019). Our study also reveals that perceived complexity is influential for resisting IoMT. Due to the novelty of IoMT and lack of experience, healthcare practitioners need to put a lot of cognitive efforts to learn how to use this technology (Mani & Chouk, 2018; Qureshi & Krishnan, 2018). In line with Cenfetelli and Schwarz (2011), we argue that healthcare practitioners have concerns about being forced to repeat steps because of using a new technological system. Similarly, our results show that process uncertainty is another concern for using IoMT. This explains that practitioners do not perceive IoMT as a transparent technology, whereas they feel ambiguity in understanding how this technology works, what are its main performance criteria, and how it integrates with other systems (Cenfetelli and Schwarz, 2011). Deceptiveness is another significant reason for resisting IoMT, as healthcare professionals have concerns about the accuracy of IoMT information that may mislead them in their decisions (Wang & Benbasat, 2016). Finally, as per the status quo bias theory (Samuelson & Zeckhauser, 1988), our results show the importance of inertia in resisting IoMT, when users find it is not compatible with their routine behaviour.

In addition, we realize that compatibility, convenience, reliability, besides information accuracy and completeness were among the reasons against factors that have substantial negative effects on scepticism and resistance toward using IoMT. Our results, consistent with prior work on innovative technologies (e.g., Rogers, 2003; Cluady, 2015), show that if healthcare practitioners find smart healthcare devices as compatible, well-matched with their current work practice and experience, it is less likely to resist using them. Saving time and effort has been previously discussed as the primary reasons for using novel technologies (Berry et al., 2002), likewise, we maintain that if IoMT provides a convenient way of working, users will use it more voluntarily. Following Everson et al. (2014), our findings indicate that IoMT reliability in providing promised services may decrease users' resistance. We also discuss that legacy health systems cannot easily guarantee the patient record completeness, (Nasir et al., 2016), thus, IoMT information accuracy and completeness would increase users' adoption likelihood. Finally, our empirical analysis acknowledges that users would resist less if they realise that IoMT is efficient in enhancing their distinctive personal and social image (Tian et al., 2001).

Contrary to our expectations, the results do not support the impact of information overload on IoMT usage resistance. We thus discuss that due to the complex nature of decision-making in healthcare (Kuziemsky, 2015), users' need to access as much as relevant data to improve the quality of their diagnosis and care plan (Kim & Kwon, 2019). Moreover, we affirm that the flexibility of IoMT is not an influential factor for users' resistance. We suppose that as accuracy and precise data collection and diagnosis are the basic qualities of IoMT (Papaioannou et al.,2020), smart devices in healthcare look rigid to healthcare professionals. Our findings also indicate that IoMT devices as professional technologies do not encompass any hedonic values for their users. Finally, in accordance with Rahman et al. (2016) study in the context of health information systems, our data analysis confirms that self-efficacy does not influence IoMT resistance. This empirical finding again emphasises that self-efficacy is a situation-specific perception that needs consideration based on the context.

Another salient finding from net effect analysis is that mostly the impacts of *reasons for* factors are stronger on resistance to using IoMT than scepticism toward IoMT, whereas the effects of *reasons against* are more significant on scepticism than resistance. This finding is in line with one of the tenets of prospect theory, which posits that people are more sensitive to losses than gains (Kahneman & Tversky, 1992).

All fsQCA solutions indicate that the presence of *reasons for* and absence of *reasons against* are the elements of a causal recipe for high scepticism and resistance. Our fsQCA solutions are roughly in accordance with net effect analysis findings, thereby, implying the validation of our multi-analytical results. Further, the configurational analysis yields new insights that enable us to enhance our understanding of the causal patterns of system, information and individual *reasons for* and *against,* as well as scepticism and resistance, and thus complements the analysis of net effects (Leischnig et al., 2016). Whereas net effect analysis recognizes a single solution for each of the outcomes, configurational analysis uncovers various equifinal paths consisting of system, information and individual attributes that lead to scepticism and resistance toward using IoMT. Specifically, in high scepticism configurations, four *reasons for* factors including perceived security risk, perceived complexity, process uncertainty, and deceptiveness, besides three *reasons against* factors (i.e. compatibility, convenience, and information accuracy) are significant conditions. However, these conditions need to be tied with complimentary conditions to result in scepticism. Moreover, necessity and paths analysis indicate that the lack of convenience and information accuracy are necessary conditions for high scepticism. Hence, we discuss that typically healthcare practitioners suffer from the lack of time (Mesko & Győrffy, 2019), and if new system saves time and energy (Chan et al., 2010) and provide them with accurate information (Hajiheydari & Ashkani, 2018; Zheng et al., 2013), they would evaluate it more positively. In configurations for low scepticism, system-related conditions (perceived security risk, perceived complexity, effort redundancy, process uncertainty), and deceptiveness are among important *reasons for* conditions.

Moreover, among *reasons against* conditions, compatibility, convenience, information assurance, information completeness, and need for uniqueness are salient for leading to the outcome. Noticeably, the presence of *reasons for* and lack of *reasons against* system-related factors are the main conditions in these configurations. This is consistent with previous studies that when system qualities of a digital health technology fit with healthcare practitioners' expectations and requirements, they would have more positive attitudes towards adopting it (Salleh et al., 2016). Further examining causal paths to the low level of scepticism highlights that information related factors are important conditions in decreasing scepticism of hospital users toward using IoMT. Of particular interest in the findings of high and low scepticism configurations is that information accuracy is an essential condition in all of the solutions, while the role of the other two necessary conditions changes across the high and low paths. For example, lack of perceived complexity is a core, essential condition in all solutions for low scepticism, but its presence is complementary in two configurations leading to high scepticism. Similarly, lack of convenience is a dominant and essential condition for all paths to high scepticism, but its presence is complementary in two configurations leading to low scepticism.

The findings suggest five configurations for high resistance to use IoMT. Each of these configurations typically reflects different clusters of healthcare practitioners' main concerns in using IoMT. For instance, in one of these configurations (H1), concerns about IoMT system-related factors whether as *reasons for* or *reasons against* are important attributes for hospital users. In other paths, individual-related factors (H4), and information related factors (H5) are the main factors to resist using IoMT. This finding indicates that there are equifinal causality pathways to resistance, as different groups of users pay attention to various factors in their decisions whether to use IoMT or not. In different configurations for high IoMT resistance, scepticism, perceived security risk, perceived complexity, process uncertainty, deceptiveness, and also lack of convenience and information accuracy have stronger causal relationships with the outcome. However, these conditions need to complement the combination of other factors in five configurations to sufficiently explain the resistance. This finding shows that the effect of system, information and individual-related factors are contingent on the status of each other, which manifests conjunctural causality in the configurational approach. In three paths to low resistance, system-related reasons for conditions and lack of information related reasons against conditions play effective roles in shaping low IoMT resistance. Specifically, the lack of perceived security risk, perceived complexity, and process uncertainty, as well as the presence of compatibility, convenience, and information accuracy are salient conditions for low resistance. We thus propose that resolving concerns about system factors and improving information conditions facilitate reducing resistance to using IoMT among healthcare practitioners.

5.2. Theoretical implication

This empirical study offers four contributions by developing and testing a model based on behavioural reasoning theory, which predicts underlying reasons drive behaviours of healthcare practitioners toward IoMT. First, in this paper, we addressed a gap in the extant literature on IoMT and IoT in general where there is a lack of theoretically grounded and empirically tested models to understand their usage behaviour (Delgosha et al., 2021). The findings improve our understanding of IoT related technologies adoption (Canhoto & Arp, 2017; Mani & Ckhok, 2018; Mital et al., 2018) by focusing on IoMT as a technological revolution in the healthcare industry and examined the impacts of its usage inhibitors and enablers simultaneously in our proposed theoretical framework. This research is among the first studies that theoretically and empirically examines healthcare practitioners' perceptions towards using IoMT. The results of our study extend our understanding of scepticism and resistance intention of IoMT users. It is very important to predict healthcare workers' behaviours in using connected smart devices, especially during pandemic health crisis (e.g. Covid-19).

Second, this study applies behavioural reasoning theory to advance our understanding of IoMT scepticism and resistance responses based on dichotomous forces (reasons for and against) that support or negate a user's logical decision making. We extend the extant knowledge by developing a theoretical model of reasons for and reasons against factors that healthcare practitioners consider when they make decisions about using IoMT. While most of the previous studies on resistance only included inhibitors of using new systems (Laukkanen, 2016; Mani & Chouk, 2018), our research, by differentiating reasons for and against factors, which are not just opposite of each other, reveals that user resistance behaviour is a function of both these dichotomous factors. Our findings show that although healthcare practitioners consider the benefits of IoMT (reasons against resistance), they have important concerns (reasons for) to be sceptical towards IoMT and decide to reject it. This important finding is in line with Claudy et al. (2015) study that argues the inherent differences between reasons for and reasons against adopting innovations. They discussed that reasons for and reasons against adopting an innovation are qualitatively dissimilar and influence users' decisions in different ways. Similarly, Delgosha and Hajiheydari (2020) discussed that considering only enablers or inhibitors effects on users' behaviour would result in an incomplete and fragmented understanding of why users adopt or resist a novel technology. Therefore, drawing on Westaby (2005) behavioural reasoning theory, in this study, we simultaneously examined promoting and inhibiting reasoning mechanisms that determine the ultimate cognition and decision of users.

Third, considering the call for asymmetrical analysis of user resistance (Hsieh & Lin, 2018), our study utilizes a novel theoretical perspective by taking a holistic view to analyse both independent, additive, symmetrical effects besides conjectural, equifinal, asymmetrical configuration. The net effect analysis assists us in explaining the distinct effects of reasons for motivating pro/anti resistance behaviour. The configurational analysis provides a deeper understanding of the combinatorial effects of reasons that mutually generate high or low IoMT resistance behaviour. The configurational approach that we used in this paper for studying asymmetrical resistance behaviour, contrasts sharply from prior studies, which are mainly based on the net effect analysis. Applying fsQCA assists us to explore how complex causal patterns of system, information, and individual conditions affect scepticism and resistance towards IoMT and what asymmetric relationships exist between them.

Finally, this study contributes to the literature by explaining healthcare providers' scepticism versus their resistance towards using IoMT. Our results highlight concerns (reasons for) are more salient for resistance than for scepticism. This finding shows that when users are close to the action (using IoMT) barriers have stronger effects on their decision than when they perceive using it psychologically distant, and they just have some general feelings (here scepticism) about it. In addition, findings indicate the significance of system-related factors such as perceived security risk or perceived complexity in generating high scepticism, while information related factors such as information assurance and completeness have substantial effects on low scepticism. Further, results of configurations for resistance describe various groups of healthcare practitioners with different concerns related to using IoMT. For some users, system-related factors are more important than others, whereas, for other groups, information or individual related factors are more salient. This finding shows that there is not one universal prescription for reducing the concerns of all users.

5.3. Practical implications

IoMT, with its enhanced capabilities, offers new opportunities for healthcare providers to improve patient care and manage the inherent complexity of healthcare, via automation, improved data, and services. For instance, in the case of Coronavirus outbreak, we expect that using IoMT devices for early identification and advanced tracing and screening could positively contribute toward avoiding the further virus outbreak. IoMT has great potentials in accelerating workflows, improving data transition, and generating value-added services for patients. Yet, these smart devices cannot be successfully implemented in healthcare contexts unless health practitioners incline to use them. Hospital users may resist using IoMT devices because of the wide and diversified ranges of reasons. We consider resistance to the change (here using technological devices in hospital work practice) as a likely reaction that managers should understand and handle.

This study proposes a better insight into the dynamism of user-IoMT that could lead to enhanced introduction strategies by managers. Understanding users' decision-making rationality based on the behavioural reasoning theory could clearly explain their justification for resistance. This knowledge helps both IoMT providers and hospital managers to realize the most influential antecedents of user resistance. The results show that system-related reasons play an essential role so that resolving system-related issues especially complexity, process uncertainty and security problems should be priorities for system developers. Healthcare practice is inherently complicated, as it requires a holistic understanding of the complex interactions and relationships while performing the right thing at the right time for diverse patients. Thus, IoMT systems are expected not to add to this complexity and possibly reduce the care process uncertainty. Using IoT applications in health data sensing, collecting and communicating makes patients' data conspicuous mark for cybercriminals and hackers. Security risks and privacy concerns in health-related systems are major concerns for healthcare providers in using IoMT devices for healthcare services. Therefore, technology providers are proposed to precisely address data privacy issues and ensure patient's information security and validity in a networking environment. Moreover, the information-related factors, especially information accuracy in positive path and deceptiveness in negative path are crucial from practitioners' viewpoint. Not surprisingly, accurate and complete information about patients is crucial for accurate and effective caring practice, while it also reflects the quality measures of the system and predicts deceptiveness in IoMT.

Moreover, hospital managers can follow some important tips in selecting and introducing IoMT solutions to decrease healthcare practitioners' resistance. As effectively introducing innovative technologies such as IoMT is an important step toward its success, managers should avoid selecting complicated systems. They also should decrease the perceived uncertainty by planning and implementing effective training and communication schemes. We suggest that selecting less-complex systems and reassuring staff about the process of health service delivery after implementation of the system will decrease scepticism and resistance amongst the hospital practitioners. Indeed, besides introducing the benefits, affordability and simplicity of using IoMT, managers should convince staff that implementing new systems will not negatively affect their professional diagnosis and care routines. In the solution selection process, paying attention to security and data breaches are also very fundamental, as healthcare data is categorised as highly sensitive data. Therefore, we suggest that selecting a simple solution besides a reliable provider, which can guarantee the security and information quality of IoMT solutions, is a big step toward successful implementation. Moreover, to address individual-related inhibitors, hospital managers can start implementing IoMT with engaging uniqueness seekers. We thus propose that managers should choose some IoMT champions who will eagerly use smart devices at work. This group will then promote the widespread implementation of IoMT solutions in their hospitals and among their peers.

5.4. Limitation and future research

Despite its contribution to theory and practice, this empirical study has some limitations to be addressed by future studies. First, our study is based on the data obtained from a self-reported survey by medical staff. We thus did not consider other users of IoT applications or other types of IoMT users in different contexts. Empirically re-examining our proposed framework in different settings, for example, in other countries or other applications like home healthcare to check the generalisability of our results or to identify contextual differences is a future research avenue. Second, fsQCA results rely on extant literature and prior knowledge to select appropriate antecedents and outcomes (Wang et al., 2019). In this study, we developed our conceptual model based on previous literature on resistance to innovation, thus future research could employ an exploratory approach or a mixed-method design to identify context-specific variables and conditions that might have an impact on this field. Also, while our theoretical model is focused on resistance toward using IoMT, future studies can specifically concentrate on understanding the effect of IoMT related techno-stressors in both positive and negative paths (Califf et al., 2020) and discuss its implications on healthcare staff post-adoption behaviours. We suggest conducting a longitudinal study to examine the users' perception after implementing IoMT and considering the construal theory (Trope & Liberman, 2010) on users' decisions for future research. Finally, we scrutinized system, information and individual reasons in this study, while contextual factors such as organisational and environmental are discussed as influential antecedents of technology diffusion (Hajiheydari et al., 2018). Future studies can be designed to understand how IoMT successful implementation could be affected by such contextual aspects, especially by comparing the results in different settings.

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Appendix 1: Survey Instrument and Construct Reliability Results

Construct/ Items	Mean	SD	Factor Loading	CR	AVE	α
Compatibility				0.78	0.79	0.87
To use IoMT, I don't have to change anything I currently do	3.78	1.42	0.73			
Using IoMT doesn't require significant changes in my existing work routine	4.15	1.35	0.84			
Using IoMT fits the way I do my work	4.23	1.15	0.91			
Convenience				0.83	0.85	0.81
Using IoMT makes doing my job easier	3.36	1.12	0.83			
Using IoMT allows me to save time, when doing my job	4.27	1.34	0.76			
Using IoMT enables me to do my jobs quickly	4.38	1.08	0.89			
Reliability				0.87	0.92	0.84
I think IoMT doesn't fail while I am working with it	4.12	1.38	0.82			
IoMT can do what I expect to do that	3.95	1.53	0.77			
IoMT delivers the services that is made for	3.87	1.46	0.89			
Flexibility				0.9	0.86	0.85
IoMT is versatile in addressing needs as they arise	3.93	1.67	0.86			
IoMT can flexibly adjust to new demands and conditions	3.45	1.42	0.8			
IoMT can be adapted to meet a variety needs	3.35	1.18	0.88			
Information accuracy				0.93	0.87	0.75
The outputs of IoMT are correct and meaningful	5.21	1.88	0.92			
The information provided by IoMT is accurate	5.12	1.56	0.87			
The Information I obtain from IoMT is error-free	5.36	1.74	0.82			
Information currency				0.79	0.85	0.87
IoMT provides me with the most recent information	5.43	1.22	0.82			
IoMT produces the most current information	4.87	1.76	0.77			
The information from IoMT is always up to date	4.55	1.45	0.85			
Information completeness						
IoMT provides me with a complete set of information	4.92	1.85	0.92			
IoMT produces comprehensive information	4.35	1.47	0.89			
IoMT provides me with all relevant information I need	4.17	1.36	0.83			
Perceived enjoyment				0.92	0.77	0.78
I enjoy using IoMT	3.72	1.67	0.82			
Using IoMT is an exciting experience	2.85	1.54	0.77			
Using IoMT is pleasant	3.87	1.17	0.85			
Need for uniqueness				0.78	0.83	0.86
Using IoMT helps me to establish a distinctive image	5.05	1.8	0.72			
Using IoMT is in line with improving my personal uniqueness	5.23	1.65	0.87			
Using IoMT helps me to shape a more unusual personal image	4.97	2.02	0.75			
I actively seek to develop my personal uniqueness by using IoMT	4.85	1.88	0.73			
Self-efficacy				0.85	0.77	0.76
It's easy for me to use IoMT	5.57	1.07	0.93			
I can completely use IoMT if there is no one around to tell me what to do	4.56	1.45	0.85			
I can use IoMT if I can contact someone if I get stuck	5.13	1.75	0.78			
Perceived security risk				0.91	0.87	0.88
The risk of an unauthorized access to critical information, while using IoMT is high	5.35	1.23	0.81			
The abuse risk of information is high, when using IoMT	4.76	1.67	0.75			
I think using IoMT is not safe and secure	5.08	1.42	0.77			
Perceived complexity				0.91	0.84	0.78
IoMT is difficult to use	4.18	1.13	0.83			
Using IoMT in healthcare service providing is a complicated process	4.76	1.37	0.77			

I think learning how to use IoMT is difficult and confusing	4.45	1.05	0.79			
Effort redundancy				0.87	0.85	0.75
IoMT requires unnecessary repetition of already preformed steps	5.42	1.17	0.85			
Using IoMT requires entering unnecessary information	5.67	1.26	0.72			
IoMT keeps the previous records, which makes my job easier ®	4.46	1.35	0.79			
Information overload				0.86	0.83	0.81
IoMT provide too much information	3.46	1.32	0.73			
Finding the relevant information is hard in IoMT outputs	4.37	1.24	0.86			
The amount of information outputs are overwhelming	4.45	1.18	0.79			
Deceptiveness				0.92	0.84	0.83
Information provided by IoMT is sometimes misleading	4.22	1.37	0.82			
IoMT does not always provide the information that it should be	3.95	1.55	0.87			
Information provided by IoMT is sometimes distorted	3.78	1.49	0.79			
Inertia				0.86	0.85	0.85
I generally consider the change as a negative thing	3.85	1.66	0.86			
I'd rather do the same old things than try new ones	3.76	1.42	0.81			
In my opinion, past technological products were satisfactory so far	3.35	1.19	0.87			
Psychological reactance				0.94	0.88	0.79
I think using IoMT causes we be tied to the system	3.23	1.02	0.93			
I think with IoMT managers want to control us	3.15	1.77	0.87			
I think, by using IoMT, my freedom at work will be limited	3.09	1.75	0.81			
Scepticism towards IoMT				0.79	0.85	0.87
I am sceptical toward IoMT devices	2.97	2.03	0.82			
I don't think IoMT will be successful	3.07	1.85	0.77			
I doubt that IoMT can actually do what the manufactures promise	3.18	1.72	0.85			
Resistance to use IoMT				0.9	0.87	0.91
In sum, using IoMT causes problems that I don't need	3.13	1.08	0.93			
I'm likely to be opposed to the use of IoMT	3.27	1.12	0.87			
It's unlikely I use IoMT in my job	2.87	1.17	0.85			
In the near future, using IoMT would be connected with too many uncertainties	3.45	1.21	0.82			
I would be making a mistake by using IoMT	3.07	1.15	0.84			

Appendix 2: The Results of Testing Mediated Effect of Scepticism

To examine whether the impact of reasons for and against is mediated by scepticism, a bootstrapping approach was employed (Hair Jr et al., 2016; Preacher and Hayes, 2008). We used the parameter estimates from the bootstrapping procedure in PLS, based on a resampling of 5000 subsamples, and calculated the standard error of each mediation effect.

Reasons	Level	Variables	Direct Effects	Indirect Effects	Total Effects	Bias corrected 95% confidence interval	Conclusion
For	System	Perceived security risk	0.28**	0.03	0.31**	[0.053–0.110]	supported
		Perceived complexity	0.41**	0.04	0.45**	[0.022–0.104]	supported
		Effort redundancy	0.18*	0.01	0.19*	[0.015–0.223]	supported
		Process uncertainty	0.14*	0.12	0.26**	[0.048–0.361]	supported
	Information	Information overload	0.06	0.01	0.07	[-0.012–0.047]	not supported
		Deceptiveness	0.44**	0.06	0.45**	[0.041–0.203]	supported
	Individual	Inertia	0.21**	0.13	0.24**	[0.032–0.161]	supported
		Psychological reactance	0.09	0.01	0.10	[-0.027–0.012]	not supported
Against	System	Compatibility	-0.25**	0.07	-0.18*	[0.175–0.387]	supported
		Convenience	-0.33**	0.14	-0.19*	[0.202–0.407]	supported
		Reliability	-0.14**	0.03	-0.11*	[0.062–0.211]	supported
		Flexibility	-0.05	-0.04	-0.09	[-0.058–0.110]	not supported
	Information	Information accuracy	-0.23**	0.02	-0.21**	[0.142–0.361]	supported
		Information currency	-0.10	0.06	-0.04	[-0.146–0.219]	not supported
		Information completeness	-0.19*	0.08	-0.11*	[0.043–0.115]	supported
	Individual	Perceived enjoyment	0.02	0.02	0.04	[-0.192–0.017]	not supported
		Need for uniqueness	-0.11**	0.01	-0.10	[0.069–0.195]	not supported
		Self-efficacy	-0.08	0.03	-0.05	[-0.032–0.051]	not supported