Doctors' Perceptions on the Use of Internet of Things Medical Devices (IOT-MDs) for Anemic Pregnant Women:
A TAM2 Study

Reenal Jain, eClerx Services Ltd, India

Vijayakumar Bharathi S., Symbiosis Centre for Information Technology, Symbiosis International University (Deemed), India

ABSTRACT

Applying the extended technology acceptance model (TAM2), this research study examined the doctors' perceptions about acceptance of internet-of-things medical devices (IoT-MDs) technology to track and monitor the health of anemic pregnant women in remote areas. The authors used structural equation modeling on a survey data of doctors (N=153), the path analysis of which reiterated certain key considerations of TAM2. The results showed that perceived ease of use has a significantly high impact on behavioral intentions of the doctor. Result demonstrability had an indirect impact on the doctor's intention to use IoT-MDs if mediated through perceived usefulness. This paper discussed research implications before stating the limitations and future directions.

KEYWORDS

Gynecologists, Healthcare, Intention to Use, Pediatricians, Perceived Ease of Use, Perceived Usefulness, Results Demonstrability, Technology Acceptance Model

1. INTRODUCTION

Based on reported statistics of world health organization (WHO), anemia, the most common ailment related to nutrition in the world today, is affecting an average of 56% of women in developing countries and 18% of women in developed countries (Stevens et al., 2013). In India, one of the rapidly developing countries, for example, anemia accounts for 20% of maternal deaths, making it the second common cause of maternal mortality (Black et al., 2008). During pregnancy, anemia can readily lead to low birth weight of infant, augmented danger of premature delivery, and mother-child mortality (Walker et al., 2007).

Lopez et al. (2016) note that major symptoms of anemia include a lower amount of red blood count (RBC) and iron deficiency. While many health ministries of developing countries have instituted policies to provide pregnant women with iron and vitamin supplements (Galloway et al., 2002), due to inadequate medicine and basic healthcare setups, these strategies have often been unsuccessful

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in reaching out to isolated areas (Khambalia et al., 2011). India's national program, for example, is focused on the prevention and control of anemia in pregnant women and young children below the age of five. Moreover, the same program is also designed to cover people living in the low-income (mainly rural) areas, where there is a scarcity of fortified foods.

Yet, the national reports do not provide a clear picture of the status of anemia in children residing in those areas, just general information related to stunting and underweight, which is accessible from the nation's database. One study conducted in the rural Barabanki district of Uttar Pradesh, for instance, surveyed 1200 preschool children (3-5 years of age) has concluded that 70% of these children has been reported to be anemic (Awasthi et al., 2003). Even so, while these children are supposedly covered under the Integrated Child Development Scheme (ICDS), where an auxiliary nurse midwife has been assigned to distribute iron and folic acid, costing about twenty-five (25) Indian rupees per recipient per annum, the daily ingestion from complementary foods among children aged 12 to 23 months has indicated only 11.7% of the level recommended (Gaillard et al., 2014).

1.1 Research Motivation and Objective

Basic medical amenities are critical; yet, these often may be limited to the more urbanized areas occupied by the multi-state and regional populations of India. Especially for those living in remote areas, there is an urgent need to address the problem of reachability (accessibility-availability) of healthcare services by studying the feasibility of integrating the technology (Internet of Things) with medical devices (IoT-MDs). The underlying rationale is that IoT-MDs are capable of monitoring the physical world through the Internet and transforming the same real-time data into digital information (Swan, 2012; Khan et al., 2016). Moreover, an analysis of the gathered data can help draw exceptional and significant inferences for deciding actions which can improve the health status of the affected without interfering into the patients' daily routine (Bandyopadhyay & Sen, 2011; Gomez et al., 2016).

Today, the available technology can transform the entire working of the healthcare sector by creating innovative ways and better channels to improve health care, notably, increasing efficiencies in multiple areas such as analyzing huge volumes of data and reducing costs such as logistics and inventory management (WHO, 1992; Li et al., 2015; Asghari et al., 2018). In this sense, an awareness of the application and utility of IoT-MDs is crucial for smart monitoring and managing medical care remotely by doctors.

The cognizance of the doctors underpins the current study and brings out the doctor's perception by investigating the factors, which influence their perception and willingness to use IoT-MDs for healthcare monitoring of anemic pregnant women in far-flung areas. Technology and infrastructure requirements are increasing because of several factors such as an increasing demand for high quality patients' care, the scarcity of medical professionals, the rising cost of providing such care and a shortage of easy access to medical care in remote areas.

The overarching research goal may be conceived as:

- Identifying and measuring of key factors that influence Doctors' perception to adopt IoT- MDs in monitoring the health of anemic pregnant women.

The specific research questions are:

- What key factors influence the doctors' perceived usefulness about IoT-Medical Devices to Anemic Pregnant Women in remote areas?
- Do doctors' perceived ease-of-use of IoT-Medical Devices influence the perceived usefulness of IoT-MDs?
- Does the perceived usefulness of IoT-MDs affect Doctors' intention to use (adopt) the same in their profession?

Given the novelty of technology in anemic pregnant women in remote areas, this study emphasizes understanding the doctors' perception of how to apply IoTs remotely and in a timely manner to service anemic pregnant women. The aim is to apply the TAM2 model to re-affirm key factors influencing the acceptance and willingness to use the IoT-MDs by physicians for remote-healthcare monitoring. Answers to the aforesaid questions may therefore lead to the design and development of a new device capable of monitoring anemic pregnant women in the villages with poor healthcare infrastructure. As rural primary health centers are deficient in terms of doctors for handling pregnancy (pre and post) cases, this study solicited responses from pediatricians and gynecologists who attend pregnancy cases arriving from nearby villages.

The paper comprises six sections. A review of the extant literature on IoT in health care and health-oriented TAM applications is given in Section 2. Section 3 presents the research methods, explaining the conceptual models of IoT and TAM2, the hypotheses and questionnaire development, the sample selection and survey method applied. Section 4 reports the data analysis and results. Section 5 discusses the effect of considering research objectives and gaps whereas Section 6 summarizes the implications of research outcomes, the potential limitation(s) and possible future research directions.

2. LITERATURE REVIEW

We cover the extant literature from two critical perspectives, identifying the research gaps. The first section deliberates upon earlier research works on applications of IoT-MDs to reiterate the current research motivation. Technology Adoption Model (TAM) in the health care to underpin our attempt to extend its application to IoT-MDs adoption comes next. The third section enumerates the research gaps.

Gartner defines the IoTs as "a network of physical objects that contain embedded technology to communicate and sense or interact with their internal states or the external environment" (Gartner IT Glossary). The definition in this research is about healthcare application enabled via IoT-MDs for monitoring a patient's vital indicators such as glucose, blood pressure, and heart rate. The IoTs facilitate monitoring of real-time data from many sources and improve the decision-making capability of care provider organizations.

2.1 IoT-MDs Applications

We list application domains of the technology and associated benefits:

- **Medical Devices (Zhao et al., 2011; Gupta et al., 2016):** Devices used for fitness solutions via sensors which contact with the human skin. These sensors are used to track patient activities and capture data for doctors;
- **Ingestible Sensors (Swan, 2012; Islam et al., 2015):** Here, patients can swallow a pill/tablet which has an embedded technology. The sensors do not contain a battery and antenna; sensors get activated by chemical reactions of the human body fluid, which provides the required power source. The real-time medical response data collected in real-time by a sensor from a patient's stomach gets transmitted via a centralized gateway to the secured data server;
- **Wireless patient monitoring (Swan, 2012; Gubbi et al., 2013; Gope & Hwang, 2016):** Used for remote surveillance of patients' vital functions via the use of well located devices which communicate real-time health data to the caregivers.

Istepanian et al. (2011) study the implications of the IoTs in the healthcare domain and propose a generic architecture of m-IoT. The architecture comprises sensor-based computing device capable of quick identification and management of any heterogeneous connectivity environment. Telecommunication and wireless technologies such as 4G/5G and 6LoWPAN offer flexibility and "always-connectedness" to the process. The technology can be an enabler for seamless and timely communication among disabled, elderly patients, and medical care team members.

Al-Taee et al. (2015) examine a functional mobile health (m-health) system capable of remote gathering and monitoring of the patient's real-time data with clinical interaction and feedback functionality. The system observes the patient's activities with treatment plans and rule-based health indicators to generate timely warnings and pieces of advice. Satija et al. (2017) study IoT applications to monitor ECG, proposing an ECG monitoring framework enabled by IoT to analyse improvement in quality, accuracy, and reliability of an unsupervised diagnosis system.

2.2 TAM2 Model in Health Care

According to Venkatesh & Davis (2000), technology acceptance is one's opinion about whether technology applies to one's job. Demonstrability of results is about the ability of the device to present the obtained results robustly. The output quality is one's perception of how precise a system performs tasks of disease analysis, which is extremely critical for the doctor's profession. The subjective norm is one's feeling on others who are significant, impacting on one's job and thinking if one should (should not) use the technology. Image is the amount to which one believes the practice of using the technology to augment one's status within a social group (Davis et al. 1989; Chismar & Wiley-Patton, 2003).

Chismar and Wiley-Patton (2002) study TAM (TAM2) model for testing information technology (IT) adoption intentions of physicians who specialize in pediatric care and their adoption of IT. The models confirmed the usefulness and job relevance as the crucial points for the pediatricians' acceptance. Chismar & Wiley-Patton (2002) note that future research works should extend the use of TAM2 for developing technological areas in the medical arena. Martinez-Caro et al. (2018) discuss the strategies for implementing IoTs for the new generation of healthcare services in Spain. Studied from the users of internet-enabled healthcare services (N=256), these authors find that the patient's e-skills, satisfaction, and perceived usefulness are critical success factors (CSFs) of IoT adoption. The existing technology landscape is applied to analyzing both technology and users' readiness critically and they also recommend exploring new areas of IoT adoption.

There are wide applications of TAM (TAM2) to predict IT usage intentions and acceptance in various user groups including students, managers, and others (e.g., clerical and administrative staff) in an organizational or institutional setting (Osbourne & Clarke, 2006). Yet, Chismar & Wiley-Patton (2003) argue that few studies applied TAM2 for understanding IT adoption in the healthcare environment. Their study has partially supported physicians' perception to adopt internet-enabled healthcare applications. Perceived usefulness strongly predict IT usage intention. The authors provide future directions to the use of TAM2 by exploring technological and contextual dimensions in the medical sector.

Tung et al. (2008) study the impact of rising medical expenses vis-à-vis an increase in the percentage of National Health Insurance (NHI) of Taiwan. To minimize operating expenses and improve efficiency, a combination of innovation diffusion theory (DoI) and TAM has been used to explore the acceptance of an electronic logistics information system (e-LIS) for healthcare personnel. The significant findings of their study include perceived usefulness (PU), perceived ease-of-use (PEU), trust, and compatibility as substantial drivers for user-acceptance to e-LIS.

Ketikidis et al. (2012) study responses from caregivers including doctors and nurses to evaluate the success of health information technology (Health IT or HIT). They conclude that their analysis verified PEU as a significant factor; however, other variables have not been captured. Rahimi et al. (2018) conduct a systematic review of the literature on applying TAM with reference to HIS development and implementation in particular. Three major HIS application domains relating to telemedicine, electronic health records (EHRs), and mobile applications have been identified. Multiple studies have also been found to extend the original TAM model with newer variables to establish its relevance to the adoption of information and communication technology (ICT). The authors emphasize the need to explore new areas and technologies for TAM with a focus on extending the reach and enhancing the validity of the model.

Past studies have unveiled several key influencing factors on the successful adoption of IoT-MDs. Specifically, in diagnosing an anemic pregnant woman's level of awareness, doctors will often be reluctant to use IoT-MDs for patient monitoring because of their lack of technical training and knowledge on the use of these technologies (Fitch, 2004; Short et al., 2004). Yarbrough & Smith (2007) study the doctor's unwillingness to adopt modern technology for the efficient detection of certain patient conditions. They apply TAM and conclude that awareness and result validation are influencing factors on doctors' initial hesitation to adopt IT. Earlier studies have argued the relevance of key influencing factors on the use of IoT-MDs, specifically, such factors relating to ease of use, compatibility of devices, access procedures, subjective norms, image, job relevance, result demonstrability and output quality (Chismar & Wiley-Patton, 2003; Lee & Benbasat, 2004; Wu et al., 2007; Edoh et al., 2016).

Applying the TAM2 model, Nadri et al. (2018) research the acceptance of a hospital IS or HIS. Their study concludes that there is no significant impact of social influence processes in the adoption of the HIS. Moreover, variables such as PEU, output quality, and job relevance have been identified to be strong predictors when determining the intention to use the technology. In other studies, Hsieh et al. (2015) emphasize the need for enhancing technology acceptance by attending to user resistance as the critical factor in understanding adoption decisions. Their research explores resistance and acceptance factors in Taiwan for using cloud technology by combining technology acceptance and status quo bias variables. Hossain & Muhammad (2016) argue that switching costs, perceived threats, and inertia can negatively impact the relationship between the doctor's intention and resistance. Notwithstanding, they also find perceived behavior and subjective norm to impact significantly on the healthcare professionals' intention-to-use.

Ducey and Coovert (2016) also apply the TAM2 to study the acceptance of tablet computers by pediatricians (N=261). They strongly recommend the need for user-trainings before IT implementation. Winston et al. (2016) develop a conceptual model for adopting radio frequency identification (RFID) applications in hospitals. Six independent variables, namely, privacy concerns regarding surveillance and RFID devices, subjective norms, cognitive factors, perception of external control, the existence of security policy, and the persistence of data are included in their research model. They then find that awareness of the security policy and RFID captured data can positively increase the use of RFID in hospitals. These researchers believe that the outcome of their study could provide practical guidance to policymakers and hospital software systems implementers.

Table 1 summarizes key technology acceptance constructs found in past TAM-related research influencing users' perception of healthcare technology adoption. The information tabulated below forms the basis of TAM2 constructs as applied to the current study.

2.3 Research Gap to Justify Current Study

On the basis of the literature review, we discuss the research gap to be addressed by this study from two perspectives: (a) the *contextual* gap; and (b) the *conceptual* gap. Briefly, the *contextual* gap entails the application of TAM2 model to study the doctor's perception in accepting and using IoT-MDs for anemic pregnant women in remote areas whereas the *conceptual* gap explores newer avenues of adopting IoT-MDs via a broadening scope of expanding knowledge to enhance TAM2 application.

3. RESEARCH METHODS

3.1 IoT-MDs Conceptual Model

Doctor's perception of accepting and using IoT-MDs depends on PU. Put simply, IoT-MDs adoption by physicians and anemic pregnant women is mainly reliant on the psychological state regarding the

Table 1. TAM and additional constructs found in past research works

Constructs / Contributors	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
Hu et al. (1999)	Y	Y	_	_	_	_	_	_	_	_	_	_	_	_	_	_
Chismar & Wiley-Patton (2002)	Y	Y	Y	Y	Y	Y	Y	_	_	_	_	_	_	_	_	_
Chismar & Wiley-Patton (2003)	Y	Y	Y	Y	Y	Y	Y	_	_	_	_	_	_	_	_	_
Raitoharju (2005)	Y	Y	_	_	_	_	_	_	_	_	_	_	_	_	_	_
Yarbrough & Smith (2007)	Y	Y	Y	Y	Y	Y	Y	_	_	_	_	_	_	_	_	_
Tung et al. (2008)	Y	Y	_	_	_	_	_	_	_	_	_	_	_	_	Y	Y
Holden & Karsh (2010)	Y	Y	_	_	_	_	_	_	_	_	_	_	_	_	_	_
Ketikidis et al. (2012)	Y	Y	Y	Y	Y	Y	Y	_	_	_	_	_	_	_	_	_
Ducey & Coovert (2016)	Y	Y	Y	Y	Y	Y	Y	_	_	_	_	_	_	_	_	_
Rahimi et al. (2018)	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	_	_
Nadri et al. (2018)	Y	Y	Y	Y	Y	Y	Y	_	_	_	_	_	_	_	_	_

Column Legends
1 Perceive Ease of Use (*PEU*)
2 Perceived Usefulness (*PU*)
3 Subjective Norms (*SN*)
4 Result Demonstrability (*RD*)
5 Output Quality (*OQ*)
6 Image (*IM*)
7 Job Relevance (*JR*)
8 Self-Efficacy (*SE*)
9 Compatibility
10 Experience
11 Training
12 Anxiety
13 Habit
14 Facilitators
15 Trust
16 Perceived Financial Cost (*PFC*)

intention to use IoT-MDs in practice. These IoT-MDs accumulate information from remote sensors that are in direct contact with the anemic pregnant women. The accumulated data allow doctors to analyze real-time patient's conditions via a variety of mobile devices (i.e., mobiles, tablets, and laptops). Active use of IoTs is a good sign for the success of medical devices; however, one's behavioral intent to use often foreshadows one's acceptance of the technology. Some pragmatic studies in past research have proven this point.

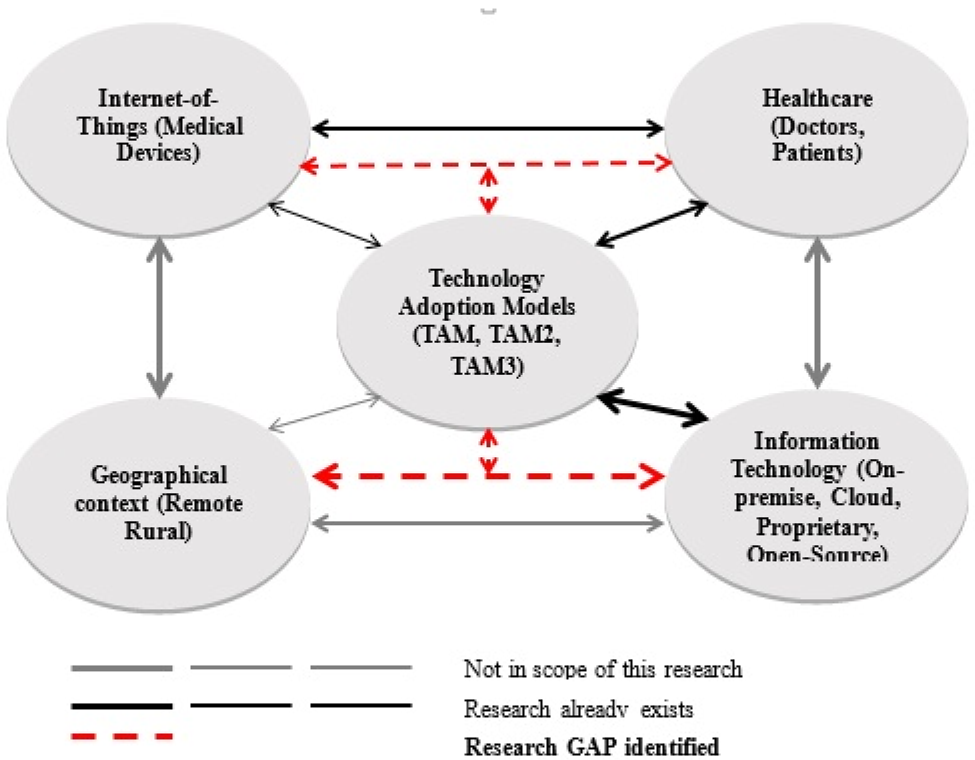
Figure 1 shows IoTs in health care, which can help to gather real-time information of anemic pregnant women via hypothetical wristband incorporating sensors (Islam et al., 2015).

The hypothetical wristband has sensors, which facilitate the transformation of captured real-world data (e.g., temperature, pressure, moisture) including personal health data (such as heart rate, oxygen saturation, blood pressure, blood glucose) into digital forms. The transmission of data via IPv6 technology consumes less power and quickly transmits the collected data from remote areas to the database(s) of medical records housed in the primary health centres for secure and well-managed storage and further analytic processing as needed.

3.2 Hypothesis Development

Past research has affirmed that the primary factor for the success of any technological device to be sustained is the user's acceptance. TAM is used to explore and explain IT acceptance and adoption

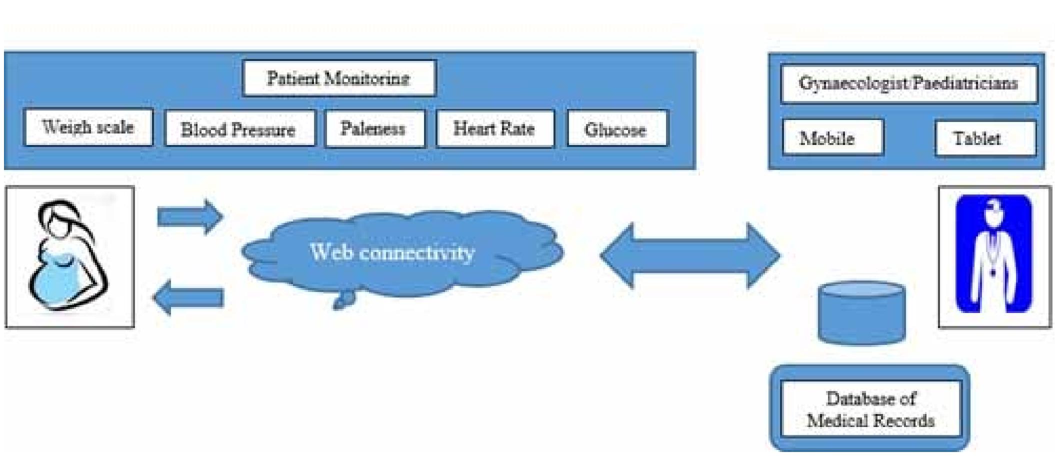
Figure 1. IoT in Healthcare (Source: Authors)



behaviors in organizations (Benbasat & Moore, 1992; Trimmer et al., 2009). TAM and TAM2 have been applied to evaluate a user's intention to use a device based on two fundamental belief factors: PEU and PU (Venkatesh and Davis, 2000).

The model comprises five constructs: perceived ease of use (PEU), perceived usefulness (PU), attitude towards using (ATU), behavioral intention to use (BI), and actual system use (AU). Notwithstanding, PU and PEU have been found to be the most common factors to informing users'

Figure 2. TAM2 conceptual model for IOT-MDs



intention towards new technology in many usage contexts, including the healthcare sector. In this research, we apply the TAM2 model via the following proposed hypotheses as depicted in Figure 2.

Contextually, PU may be defined as the amount in which a doctor believes that a particular IT product such as IoT-MDs would boost his (her) job productivity and performance to facilitate remote monitoring of pregnant women. In contrast, PEU may be deemed as the degree to which a healthcare practitioner believes that using a particular innovation would be effortless or less-effort required in anemia diagnosis. It is argued that PEU impacts the PU of such devices in the medical sector (Chismar & Wiley-Patton, 2003; Wu et al., 2007; Holden & Karsh, 2010; Hsieh, 2016). Hence the following hypotheses are advanced:

H1: PU will significantly predict doctors' Intentions to Use (IU) of IOT-MDs for monitoring pregnant women.
H2a: PEU will significantly predict doctors' IU of IOT-MDs to analyze anemia data.
H2b: PEU for analyzing anemia data will directly impact PU as it helps in remote monitoring.

Past studies state that the TAM model presents a decent clarification for judging physicians' acceptance of any IT (Yarbrough & Smith, 2007; Melas et al. 2011; Ketikidis, 2012). Many studies recommend extending the TAM model by considering different constructs that can impact the usage decision of technology in health care (Lin, 2014). Harmony, which denotes the degree to which one perceives an innovation to be consistent with prospective users, is one such characteristic (Rogers, 2010; Wu et al. 2007). For example, to assess the technology compatibility construct, Chau & Hu (2002) further combine the TAM and Theory of Planned Behavior (TPB) to assess Physicians' acceptance of telemedicine technology.

Subsequently, TAM2 has extended the scope of the original TAM model to include job relevance, output quality, result demonstrability, image, and the subjective norm (SN). SN is a physician's sensitivity that others who may be essential (i.e., family, peers & friends) and who think if the technology should or should not be used can impact the physician's job (Chismar & Wiley-Patton, 2003). We may also regard it as the adoption factor, which looks at the influence exerted by the social environment of the user (adopter); that is, people for whom the individual considers as necessary. It refers simply to the person's perception of normative social pressures and relevant others' belief if the individual (user) should adopt or not adopt the technology. The normative influence derives itself from a professional standard and network influence. The underlying premise is that how people from the same background will approach a problem, one would likely do so in the same way. These people can be professional peers, people of authority, parents, colleagues, or even subordinates (Wu et al., 2007). Accordingly, the following hypotheses are slated:

H3a: Subjective Norm (SN) will predict IU of IoT-MDs over and above the effects of PU and PEU.
H3b: SN has a direct effect on PU.

An image refers to the degree in which the healthcare professional believes the use of technology will enhance one's status within a social group. Perceptions of several people can heavily influence the impression they make or the situation they have created for themselves within their social or professional circles. For IoT-MDs, doctors may perceive that usage of these devices can boost their occupational prestige within their working environment (Banderker & Van Belle, 2009; Chismar & Wiley-Patton, 2003; Wu et al., 2007). Hence, the following hypothesis is proposed:

H4: Image (IM) pertaining to technology-savvy doctors will significantly impact PU.

Job relevance reflects the user's opinion about whether the technology applies to one's job or daily routines at work (Ketikidis et al., 2012). It helps in checking whether it causes an actual increase in a doctor's efficiency by being significant for their routine activities such as the monitoring of patients' health or the analysis of previous health data. Every future technology should align with the current work practices of doctors and significantly improves the efficiency of job routines (Banderker & Van Belle, 2009; Venkatesh & Davis, 2000; Wu et al., 2007). As such, we state the following hypothesis:

H5: Job relevance (JR) of IoT-MDs in analyzing the health status of anemic pregnant women directly impacts PU which will help to predict IU of such devices.

Output Quality (OQ) is a state of being free from defects and significant variations (fineness). Individual's perception of a medical device which can be the OQ of any technology, judged by how accurate a system performs tasks in analyzing a disease. This feature can also be verified by checking the adherence of the product to a strict and consistent commitment to the gold standards to ensure universal fulfillment of the doctor's requirement. Accurate results will exponentially increase the productivity of doctors, quality of care and treatment, enhanced effectiveness, and overall practical service (Banderker & Van Belle, 2009; Wu et al., 2007). In IoT-MDs, which is collecting essential real-time information from anemic pregnant women, OQ becomes crucial in understanding the health problems of the patient. Hence, healthcare technology must produce exact information to become acceptable by doctors, and we advance the following hypothesis:

H6: Output Quality (OQ) can increase the productivity of doctors by providing fine results directly affects PU of using IoT-MDs.

Result demonstrability (RD) is the degree to which results or benefits of using IoT-MDs are clear or demonstrated. In order words, it refers to the concreteness of the results of using the technology or how tangible these benefits are to the user (Banderker & Van Belle, 2009; Chismar & Wiley- Patton, 2003; Egea & González, 2011). Indeed, IoT-MDs are expected to improve a doctor's work, which will in turn help in the decision-making process. As the design and development of these devices are yet to be ready for anemic pregnant women, it is very important to maintain a high level of accuracy for results. The doctors' little assurance in their competency to adopt IoT-MDs and mobile computing may deprive the expected performance of the healthcare device and diminish the intention to use of IoT-MDs (Wu et al., 2007).

Hence, the following hypothesis is stated:

H7: Result demonstrability (RD) capability of IoT-MDs directly impacts PU of using IoT-MDs.

Based on the various TAM constructs discussed so far, Table 2 shows operational definitions and supporting questionnaire items predicting the effects of various constructs and their expected impact on the doctors' acceptance of IoT-MDs.

3.3 Questionnaire Development, Sampling and Survey

To validate the TAM2 model, the original questionnaire is modified to better fit the doctor's community. Hence, the following assumptions are noted expressedly:

- Without the actual technology in place, variables such as voluntariness, experience, and usage behavior are excluded. To acquaint doctors on the IT in question, an existing device such as the *Fit-bit*, an activity-tracker, wireless-enabled wearable device which monitor, measure and report

Table 2. Operationalization of TAM2 constructs

Construct	Questionnaire Items	Reference
Perceived Usefulness (PU)	**PU_1** - IOTs for rural health care could improve the quality of care that I deliver to anemic pregnant women. **PU_2** - IOT could enhance my effectiveness in the work and analysis of anemia. **PU_3** - IOT could increase my productivity in treating anemic pregnant women	(Davis, 1989; Wu et al., 2007; Raitoharju, 2005)
Perceived Ease of Use (PEU)	**PEU_1** - My interaction with IOT is/will be clear and understandable. **PEU_2** - IOT will be easy to use for rural anemic pregnant women. **PEU_3** - Interacting with IOT medical device for anemia will not require a lot of mental effort.	(Davis, 1989; Venkatesh & Davis, 2000; Holden & Karsh, 2010)
Subjective Norm (SN)	**SN_1** - Doctors who influence my behavior think I should use IOT for rural anemic pregnant women. **SN_2** - Doctors who are important to me think I should use IOT for rural anemic pregnant women	(Venkatesh & Davis, 2000; Chismar & Wiley-Patton, 2002; Rahimi et al., 2018)
Image (IM)	**IM_1** - Doctors who use IOT in rural health care have more prestige than those who do not. **IM_2** - Delivering IOT enabled treatment is a status symbol **IM_3** - Doctors who use IOT in rural health care have a high profile	(Davis, 1989; Ducey & Coovert, 2016; Ketikidis et al., 2012; Nadri et al., 2018)
Job Relevance (JR)	**JR_1** - Usage of IOT for detecting anemia is important to the delivery of health care for pregnant women. **JR_2** - Usage of IOT for detecting anemia is relevant to the delivery of health care for pregnant women.	(Venkatesh & Davis, 2000; Chismar & Wiley-Patton, 2003; Yarbrough & Smith, 2007)
Output Quality (OQ)	**OQ_1** - The quality of anemic health information collected through IOT is high. **OQ_2** - I expect the quality of future IOT medical devices to be high. **OQ_3** - The quality of professional information collected through IOT is high.	(Davis, 1989; Wu et., 2007; Chismar & Wiley-Patton, 2003; Ketikidis et al., 2012; Rahimi et al., 2018)
Results Demonstrability (RD)	**RD_1** - IOT medical device could reduce the cost of my care delivery. **RD_2** - I believe I could communicate to others the consequences of using IOT for pregnant women. **RD_3** - I would have difficulty in explaining why using IOT in rural health care may or may not be beneficial.	(Venkatesh & Davis, 2000; Wu et., 2007; Ducey & Coovert, 2016; Nadri et al., 2018; Chismar & Wiley-Patton, 2003)

personal health data on specific metrics (e.g., *calories burnt, heart rate, sleep quality, blood pressure*), is established as a baseline. Thus, questions asked in future tense will keep reference to the current technology; notably, the PU and PEU variables make assumptions that doctors have partial knowledge about using the IT in question (Chismar & Wiley-Patton, 2003);

- As the dialysis of disease is critical, OQ plays a significant role; thus, additional OQ questions are included following the doctor's input via the pilot;
- Re-phrasing of all questions to include doctors' nomenclature;
- 5-point Likert-type scale (1 = strongly disagree, 2 = disagree, 3 = neutral, 4 = agree and 5 = strongly agree) to be used consistently;
- Random sequencing of questions to reduce probable ceiling (or floor) effect that persuades monotonous responses to items intended to measure a specific construct.

Table 3. Demographic characteristics of respondents

Characteristics	Items	N*	%	Cumulative %
Specialization	Gynecology	69	45.1	100.00
	Pediatrics	84	54.9	
Experience	Less than 5 yrs	60	39.2	100.00
	5-9 yrs	15	9.8	
	9-14 yrs	26	17.0	
	14-19 yrs	30	19.6	
	20-24 yrs	11	7.2	
	More than 24 yrs	11	7.2	

The survey instrument has been differentiated via three (3) segments: (a) general questions; (b) demographic questions; and (c) TAM2 model questions. Twenty-one (21) questions measuring seven latent variables are included in the final instrument. Two hundred (200) subjects (gynecologists and/or pediatricians) affiliated with medical institutes and hospitals in India are administered the questionnaire, of which one hundred seventy-three (173) have responded. Nineteen (19) responses among these are subsequently excluded for various reasons, including having wrong or incomplete answers as well as answers that did not meet the criteria of the construct being investigated. The final sample size comprises one hundred and fifty-three (153) valid responses.

We impose no time limits on any of the respondents to complete the survey questionnaire so as to keep the data unbiased, accurate and clean. Completion time ranges between five (5) to seven (7) minutes. The review process to refine the questionnaire has been piloted until no further modification is needed as of October 2017. Then, both online and offline methods are employed to circulate and administer the survey. The survey administration ran from November 2017 to August 2018 with completed questionnaires accumulated to end of August 2018. We code response options on a 5- point continuous scale (1 = lowest, 5 = highest) with the higher scores reflecting greater perceived-potential-use of IoT-MDs.

4. DATA ANALYSIS AND RESULTS

Table 3 presents the demographic characteristics of the 153 respondents.

Cronbach alpha value measures the reliability and validity of the data, and Structural Equation Modeling (SEM) is used to examine the studied model (Wong, 2013). We apply SmartPLS3 software to conduct the experiments. The sub-sections explain the analysis.

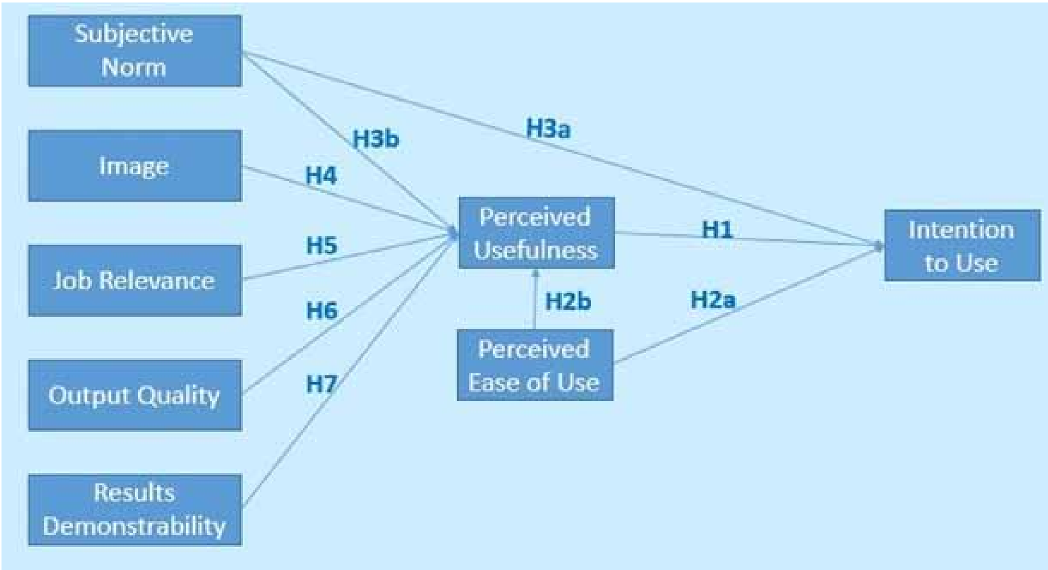
4.1 Target Endogenous Variable Variance

An endogenous variable can explain the relationship between variables and the study model as they show whether a variable causes a particular effect. This effect explicates the model to explain outcomes on dependent variables based on the impact of independent variables.

In our study model, the dependent variables are PU and PEU. Job Relevance (JR), Image (IM), Result Demonstrability (RD), Output Quality (OQ), and Subjective Norms (SN) are independent constructs. All of these constructs will predict behavioral intention to use (IU), which is again an dependent variable.

Results of our analysis show that the coefficient of determination, R square = 0.321 for the PU endogenous latent variable. This means that the five (5) latent variables (SN, IM, JR,OQ and RD) explain 32.1% variance in PU, which is moderately low (Refer to Figure 3). As well, PU, PEU, and

Figure 3. Inner model path coefficients



SN explain 12.4% of the variance of IU; thus, it is not clear how these three constructs impact on the final variable, and the outcome cannot be convincingly predicted.

4.2 Inner Model Path Coefficient Sizes and Significance

Inner path model defines the relationship among the latent variables that create the entire structure.

From Figure 3, the relationship coefficient of PEU and IU is 0.349, which is statistically significant. Thus, PEU has the most potent effect on IU, which is approximately 35%. However, the hypothesized path relationship between PU and IU is not statistically significant as the relationship coefficient is 0.068, which is significantly lower than 0.1.

Thus, we can infer that:

PEU is a moderately strong predictor of IU; but, PU does not predict the IU.

4.3 Outer Model Loadings

Outer Model represents the relationship between latent variables and their indicators. Table 4 illustrates the model loadings represented by the paths from a construct to its representative indicator variables. The larger the loadings, the stronger and more reliable is the measurement model.

The value of loadings closer to 1.0 implies that the latent variable is more reliable. Based on information provided in Table 4, we can conclude that the model is reliable and significant as all values are over 0.7.

4.4 Indicator Reliability

Table 5 represents the cumulative values of R square, Average Variance Extracted (AVE) and Cronbach's alpha. Indicator reliability helps to determine variables dependency on its characteristics.

As shown, the square of each of the outer loadings lies in between 0.48 to 0.92, which means that the indicator reliability value is high. All of the outer loading values are much larger than the minimum acceptable level of 0.4 (being close to the preferred level of 0.70), which shows the reliability of the latent variables.

Table 4. Outer model loadings

	IM	*IU*	*JR*	*OQ*	*PEU*	*PU*	*RD*	*SN*
IM_1	0.9272							
IM_2	0.9388							
IM_3	0.9316							
IU_1		0.9103						
IU_2		0.9144						
JR_1			0.9202					
JR_2			0.849					
OQ_1				0.7097				
OQ_2				0.9117				
OQ_3				0.8874				
PEU_1					0.6974			
PEU_2					0.822			
PEU_3					0.875			
PU_1						0.7671		
PU_2						0.8894		
PU_3						0.7429		
RD_1							0.8786	
RD_2							0.8468	
RD_3							0.7735	
SN_1								0.9602
SN_2								0.9421

Table 5. Indicator reliability

	AVE	Composite Reliability	R Square	Cronbach's Alpha	Communality	Redundancy
IM	0.8696	0.9524		0.9262	0.8696	
IU	0.8324	0.9085	0.1238	0.7987	0.8324	0.0981
JR	0.7837	0.8786		0.7296	0.7837	
OQ	0.7075	0.8776		0.7855	0.7075	
PEU	0.6425	0.8424		0.7229	0.6425	
PU	0.6438	0.8434	0.3211	0.7303	0.6438	-0.0023
RD	0.6958	0.8725		0.7862	0.6958	
SN	0.9048	0.9500		0.8957	0.9048	

Table 6. Fornell-Larcker criterion for checking discriminant validity

	IM	*IU*	*JR*	*OQ*	*PEU*	*PU*	*RD*	*SN*
IM	**0.93252**							
IU	0.1573	**0.9123**						
JR	0.0932	0.1273	**0.88526**					
OQ	0.4251	0.1073	0.2635	**0.8411**				
PEU	0.3357	0.3434	0.3277	0.3861	**0.80156**			
PU	0.2038	0.196	0.3348	0.3006	0.4399	**0.80237**		
RD	0.217	0.2186	0.4092	0.4706	0.3949	0.462	**0.834146**	
SN	0.4283	0.1371	0.0802	0.3282	0.5168	0.3759	0.369	**0.95121**

4.5 Internal Consistency Reliability

We apply the internal consistency reliability to examine the correlations between different variables. In Table 5, the Cronbach's Alpha values are significantly higher than 0.7, proving high reliability.

Moreover, composite reliability should be 0.7 or higher for concluding the reliability of the model. As all relevant values are larger than >0.8, so the analysis has generally shown high levels of internal consistency reliability among all of the reflective latent variables.

4.6 Convergent Validity

We calculate convergent validity to measure how two theoretically related constructs relate statistically.

To check convergent validity, we tested each latent variable's AVE. Table 5 states that all the AVE values are greater than the acceptable threshold of 0.5; thus, the analysis results confirm convergent validity.

4.7 Discriminant Validity

We examine discriminant validity to test whether variables that are not supposed to be related are unrelated (Fornell & Larcker, 1981; Anderson & Gerbing, 1982; Hult & Ketchen Jr, 2001). The square root of each AVE in each latent variable can establish discriminant validity if these values are greater than other correlation values among the latent variables.

As shown in Table 6, all the square root values lie in between 0.80 to 0.95, which are greater than the inter-correlations of the eight latent variables. Hence, we have established discriminant validity.

The latent variable correlations presented in Table 7 shows that the constructs of the model do not have any instances of multicollinearity, which does not disturb the consistency and unbiasedness of the constructs.

4.8 Checking Structural Path Significance in Bootstrapping

The bootstrapping algorithm took sub-samples from the original sample to identify standard errors and performed the *t-statistic* test for significance of both inner and outer model. Bootstrapping provides a means to manage distortion in the sample data, which cannot fully represent the entire dataset. Hence, bootstrapping can show strength in dealing with non-normal and non-asymmetric distributions when no large sample size is available (Shahanaghi et al., 2012).

As provided in Table 8, the analysis result approximates the normality of data. This technique assigns measures of precision to the sample estimates by calculating sample distribution using simple methods. These simple methods estimate properties of the estimator such as variance by approximating

Table 7. Latent variable correlations

	IM	*IU*	*JR*	*OQ*	*PEU*	*PU*	*RD*	*SN*
IM	1							
IU	0.1573	1						
JR	0.0932	0.1273	1					
OQ	0.4251	0.1073	0.2635	1				
PEU	0.3357	0.3434	0.3277	0.3861	1			
PU	0.2038	0.196	0.3348	0.3006	0.4399	1		
RD	0.217	0.2186	0.4092	0.4706	0.3949	0.462	1	
SN	0.4283	0.1371	0.0802	0.3282	0.5168	0.3759	0.369	1

distribution. We use empirical distribution for approximating distribution by assuming a set of observations derived from an independent and identically distributed population. Thus, our approach creates several re-sampling of the original dataset via random sampling. This works best when the results are unpredictable or complicated. The technique uses distribution-independent procedure to assess the properties of the distribution of the primary sample to derive parameters of interest.

Path coefficients of an inner model are significant in the cases of "Perceived Ease of Use–Intention to Use" and "Result demonstrability–Perceived Usefulness" linkages as path coefficient (3.1438 and 2.3754 respectively) are greater than 1.96 (two-tailed t-test with a significance level of 5%), as shown in Table 8.

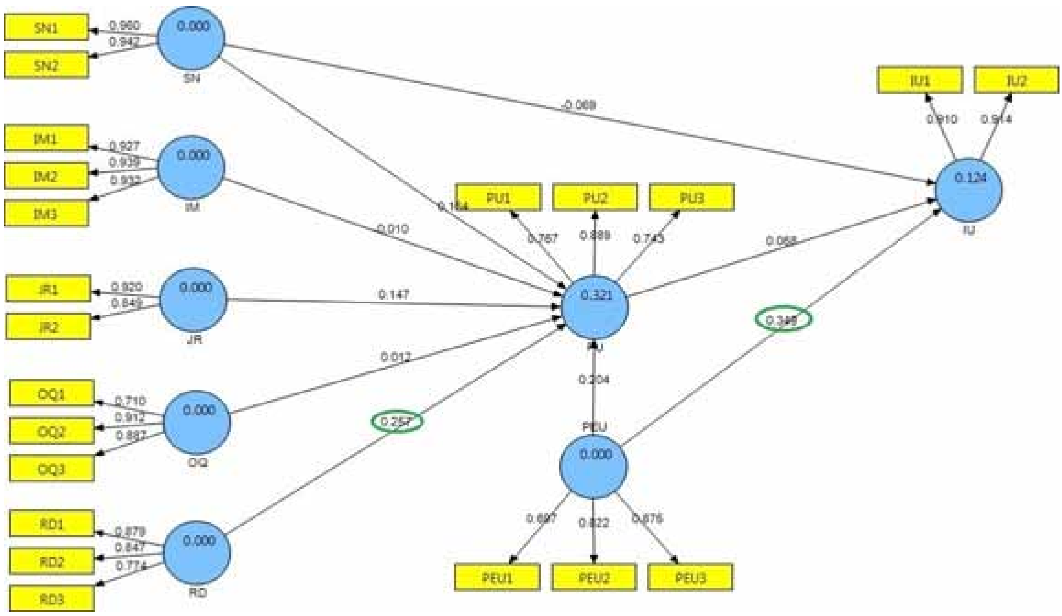
Table 8. t-statistic (INNER MODEL)

	Original Sample (O)	**Sample Mean (M)**	**Standard Deviation (STDEV)**	**Standard Error (STERR)**	**t-statistic (|O/STERR|)**	**Hypothesis Supported**
IM -> PU (H4)	-0.0096	0.0022	0.1016	0.1016	0.0944	Not supported
JR -> PU (H5)	0.1473	0.1479	0.1015	0.1015	1.4512	Not Supported
OQ -> PU (H6)	0.0124	0.0199	0.1068	0.1068	0.1162	Not Supported
PEU -> IU (H2a)	0.349	0.3562	0.111	0.111	3.1438	*Supported*
PEU -> PU (H2b)	0.2039	0.214	0.1086	0.1086	1.8772	Not Supported
PU -> IU (H1)	0.0683	0.0698	0.1085	0.1085	0.6299	Not Supported
RD -> PU (H7)	0.2569	0.2539	0.1081	0.1081	2.3754	*Supported*
SN -> IU (H3a)	-0.069	-0.0696	0.1136	0.1136	0.6071	Not Supported
SN -> PU (H3b)	0.164	0.155	0.1092	0.1092	1.5021	Not Supported

Similarly, Figure 4, Table 9 and 10 presents the *t-statistic* for outer model loadings which are larger than 1.96; hence, it is highly significant.

PEU of IoT-MDs for analyzing anemia in pregnant women directly impact PU (*H2a*) and RD capability of IoT-MDs directly impacts its PU (*H7*). There is also considerable support (path coefficients greater than 1.96) for the result that *PEU* and *RD* are the two most important determinants

Figure 4. Structural path in bootstrapping



to a doctor's behavioral intent. Indeed, the significance of *H2a* and *H7* solidify on the fact that if the IoT-MDs are what we perceived as easy to use, then this perception will positively impact the doctors' mind-set for using and adopting in their day-to-day activities. Beyond this, the devices result demonstrability capabilities will also infuse a similar impact on the mind-set of doctors.

JR, SN and *RD* impact significantly on PU. Notwithstanding, PU has a shallow impact on behavioral intent; thus, the remaining hypothesis: *H1, H2b, H3a, H3b, H4, H5*, and *H6* has little to no support from the data derived from responding pediatricians-gynecologists. One primary reason may be the absence of such a device, which could help in understanding the overall functioning of the device. Also, doctors might not relate the device with their job, which makes the hypothesis *H5* (job relevance) unsupported. Doctors do not generally perceive using new technology will raise their status in their social group as it is clear from the image's contribution to PU, making hypothesis *H4* insignificant.

Hypotheses *H3a* and *H3b* state that SN will predict IU of IoT-MDs; however, the path coefficient helps us to conclude that doctors will not oblige even if people influencing their job routines may impact their intention to use the new technology for the benefit of their patients. Thus, we understand that doctors are not bothered over their branding or overall image to an extent that it will impact upon their professional practice.

The research findings contribute to technology acceptance theory in several ways. First, the study results affirm that TAM2 model allows more or less a parsimonious approach towards examining the doctors' perception of IoT-MDs adoption. It supports the recommendations of earlier research works to apply technology acceptance studies to unexplored avenues, specifically, remote healthcare monitoring of anemic pregnant women with IoT-MDs that are unique as rolled out in the current study.

Additionally, the results also strengthen the belief that TAM2 fits well for examining the relevance of any new technology. The findings should enthuse future research works to experiment with the model with newer and customized constructs in new contexts and settings.

Table 9. t-statistic (OUTER MODEL)

	Original Sample (O)	Sample Mean (M)	Standard Deviation (STDEV)	Standard Error (STERR)	t-Statistic (|O/STERR|)
IM_1 <- IM	0.9272	0.8861	0.247	0.247	3.7543
IM_2 <- IM	0.9388	0.8949	0.2203	0.2203	4.262
IM_3 <- IM	0.9316	0.8855	0.2405	0.2405	3.8744
IU_1 <- IU	0.9103	0.9042	0.0488	0.0488	18.6489
IU_2 <- IU	0.9144	0.9152	0.0312	0.0312	29.3472
JR_1 <- JR	0.9202	0.9162	0.0748	0.0748	12.3096
JR_2 <- JR	0.849	0.8301	0.1135	0.1135	7.4805
OQ_1 <- OQ	0.7097	0.7062	0.1291	0.1291	5.4984
OQ_2 <- OQ	0.9117	0.8962	0.0862	0.0862	10.5742
OQ_3 <- OQ	0.8874	0.8695	0.0909	0.0909	9.7668
PEU_1 <- PEU	0.6974	0.6869	0.0929	0.0929	7.5076
PEU_2 <- PEU	0.822	0.8148	0.0521	0.0521	15.7771
PEU_3 <- PEU	0.875	0.8742	0.0326	0.0326	26.8365
PU_1 <- PU	0.7671	0.7603	0.0768	0.0768	9.9915
PU_2 <- PU	0.8894	0.8843	0.0301	0.0301	29.5211
PU_3 <- PU	0.7429	0.7428	0.0675	0.0675	11.0107
RD_1 <- RD	0.8786	0.8801	0.0354	0.0354	24.8222
RD_2 <- RD	0.8468	0.8304	0.0742	0.0742	11.4135
RD_3 <- RD	0.7735	0.7652	0.0809	0.0809	9.5624
SN_1 <- SN	0.9602	0.9605	0.0109	0.0109	87.8057
SN_2 <- SN	0.9421	0.9392	0.0225	0.0225	41.8665

5. DISCUSSION

TAM is a well-established model to predict the acceptance of new technology among users by studying variables which can explain human psychology. Although the evolved theory provides a decent elucidation of the constructs, yet some studies recommend the inclusion of even more constructs related to healthcare when studying emerging technologies being applied in the healthcare domains. The reason for more such mediating factors is to deep dive into the research to find yet hidden factors which make doctors resist the usage of new technologies.

Unfortunately, it is often difficult to include physicians and specialists in many past TAM-driven studies, especially while these are the ones who need technological aids to perform patient health critical analysis. Importantly, doctors should be supported with newer and emerging technologies and they should find these devices easy to handle, compatible with their existing work practice and to be designed appropriately to collect the precise data they need for their analysis. To date, with the trends of rapidly rising healthcare costs and aging populations across both developed and developing countries, the need to better predict the acceptance of new technology to support care practitioners in the healthcare industry has only gotten more dire and urgent (Holden & Karsh, 2010; Melas, 2011).

Additionally, a new conceptual model should integrate several independent variables specific to IoT- MDs for various sorts of patient populations, for example, *affordability, IT skills, a specific*

Table 10. t-statistic of outer loadings

	IM	IU	JR	OQ	PEU	PU	RD	SN
IM_1	3.7543							
IM_2	4.262							
IM_3	3.8744							
IU_1		18.6489						
IU_2		29.3472						
JR_1			12.3096					
JR_2			7.4805					
OQ_1				5.4984				
OQ_2				10.5742				
OQ_3				9.7668				
PEU_1					7.5076			
PEU_2					15.7771			
PEU_3					26.8365			
PU_1						9.9915		
PU_2						29.5211		
PU_3						11.0107		
RD_1							24.8222	
RD_2							11.4135	
RD_3							9.5624	
SN_1								87.8057
SN_2								41.8665

audience, secure transmission of sensitive healthcare data, an effortless analysis of the data, relative advantage and persistence of data to foster better forecasting and representation. The direction taken in our study corroborates with that conducted by Winston et al. (2016) for RFID technology usage in the hospitals with the need to incorporate new constructs. Organizational support and doctor's interest in using medical devices can also further enhance the validity of the model. Physicians are more likely to use new technology already in use or compatible with their current clinical practice (Egea & González, 2011).

Our study results show that two significant drivers explain a doctor's behavioral intention to use IoT-MDs; *PEU* and *RD,* which are consistent with prior studies by Tung (2008). The most optimum path to gain user confidence in the new system is to focus on the perceived ease of use. Results of this study confirm that *PEU* has the most potent effect on the IU, which corroborates with the earlier works of Ketikidis et al. (2012) and Nadri et al. (2018). Thus, *RD* should be an important prerequisite in the development IoT-MDs.

While IoT-MDs can increase the efficiency of the doctors, few factors are still unknown because the device is not yet ready and does not give a complete picture of its features and functionality. A critical factor in implementing the devices in rural areas is to find out the feasibility to deploy these devices due to constraints such as network connectivity issues, electric power supply issues, lack of awareness of modern technology and mobile competency among patients and doctors. Adequate training to be provided to the target audience in order to handle these devices with mobile computing capabilities can minimize such constraints. As we are targeting a particular group with less purchasing power living in rural India, *affordability* of the device is another major consideration. The success of the IoT-MDs will therefore depend if these devices are available at a cost-effective price to both doctors and patients. Switching costs and perceived threats on the sensitive healthcare data of pregnant women can negatively impact the association between a doctor's *IU*, as reiterated by Hossain & Muhammad (2016).

The *specification* (size, measurement, and weight) of the device, the relative advantage of using the device and the usual doctor's resistance to using new technologies are some of the key factors identified by Yarbrough & Smith (2007) based on research investigating the barriers restricting adoption. Also, due to time constraints on this project, an attempt to reach a wider audience faces restrictions. However, the current attempt is just an exploratory study to find the awareness and acceptance of new and evolving technology in the healthcare sector, specifically for providing care to anemic pregnant women, which has become a globally relevant problem. Hence, the development of newer devices will lead to lessen the hassles of timely healthcare monitoring.

6. CONCLUSION

To conclude, we state that growth and expansion of the IoTs based on medical devices (IoT-MDs) can change the future of the medical industry by disrupting the existing realms of distant medical care. Doctors will treat more patients in remote areas with increased work efficiency. Timely treatment with higher quality of care and medication will soon be available. In a nutshell, the emerging technologies will prevent clinical errors and death cases in developing countries such as India by notifying the patient to report quickly to primary health centers. The design of these devices should be able to address the doctor's requirements, and also profoundly empathize with patients' needs for convenience so that to increase the intent to use (or willingness to their use) and actual use (results demonstrability).

Altogether, this research may be considered to fall within a niche area and hence it has a limited generalization of results. We recommend conducting the acceptance and adoption of modern technology in various sectors with context-specific constructs along with the TAM model and its extensions. In light of this, future studies can include more factors concretely related to the IoTs, for example, electricity in rural areas, network connectivity, and affordability by economically weak users. Also, factors such as feedback from doctors, patients' awareness, and acceptance/resistance as well as IT skills may be included in further research. The current study did not capture a change in the doctor's reaction over continuing usage, specifically, the period from the earlier model to its advanced version (as their decision may get influenced by system experience). Our study will contribute to enhancing the current scope of technology adoption towards building a holistic model to address several sub-segments of healthcare in particular and other industry domains at large.

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Reenal Jain is a strong information security professional with a Master of Business Administration (M.B.A.) focused on Information Technology from Symbiosis International University. She is currently working with eClerx Service Ltd in Pune, India, where she has experience in conducting ISO 27001 internal audits, third-party vendor audits and various client audits as per MSA obligations and best practices. Passionate about exploring new technologies and keenly interested in the application of those technologies, she wants to make an impact by developing products which can address social issues.

Vijayakumar Bharathi S. (PhD) is a Post Graduate in Commerce from Bharathiar University, Coimbatore and in Management from Bharathidasan University, Trichy. He earned his PhD in Computer Studies from the Symbiosis International University (SIU), Pune in the area of ERP Risk Assessment for SMEs. He is an ICWA (Inter) Qualified from ICWA, India. He has over 25 years of experience including 5 plus years in the Industry at an Indo-Swiss JV manufacturing textile machinery. Dr. Bharathi's teaching and research interests are Financial Accounting, Intellectual Capital, Enterprise Systems, Big Data, Case-Teaching and Design Thinking.