

The Changing Paradigm of Health and Mobile Phones: An Innovation in the Health Care System

Nabila Nisha, North South University, Dhaka, Bangladesh

Mehree Iqbal, North South University, Dhaka, Bangladesh

Afrin Rifat, North South University, Dhaka, Bangladesh

ABSTRACT

This article describes how widespread adoption of mobile technology in healthcare is an innovation that is inevitable today in both developed and emerging markets around the world. Mobile health services (m-Health) act as an effective, accessible and affordable means of providing healthcare knowledge to users directly from providers. Despite such benefits of m-Health services, rapid adoption is not yet occurring, particularly in emerging markets. The main barrier is mostly the cynical behavior of users regarding this medium of healthcare services. The aim of this article is to examine underlying factors that can influence future use intentions of m-Health services. Conceptual model of the study identifies service qualities like reliability, privacy, responsiveness, empathy and information quality along with facilitating conditions, trust, effort expectancy and performance expectancy as significant constructs that influences users' overall perceptions of m-Health services, along with moderating effects of age and gender. Limitations and implications for practice and research are also discussed.

KEYWORDS

Bangladesh, Emerging Economy, Information Technology, Mobile Communications, Mobile Health Services, Service Quality, Urban Population, UTAUT

INTRODUCTION

Information and communication technology (ICT) has the ability to offer great potential for improving the quality of services provided along with the efficiency and effectiveness in health care sectors. According to Sayyahgilani et al. (2014), it can also reduce the organizational expenses by reducing processing time and human resource. Internet - which is the fastest growing aspect of ICT in history, actually serves as a tool with a huge potential for health care organizations to deliver quality and cost-effective care to geographically dispersed populations (Jung, 2008).

Today, m-Health is a new paradigm for healthcare systems, covering both processing and telecommunication technologies. The Global Observatory for e-Health (GOe) of the World Health Organization (WHO) defined m-Health as the medical and public health practice supported by mobile devices, such as mobile phones, patient monitoring devices, personal digital assistants (PDAs) and other wireless devices. The m-Health application generally provides patient monitoring, sends text messages reminding patients to take needed medications and offers suggestions for maintaining health while pregnant, even in war-ravaged places (Nisha et al., 2015). The main advantages of using mobile phones for health care services are that these devices are personal, intelligent, connected, and always

DOI: 10.4018/JGIM.2019010102

This article, originally published under IGI Global's copyright on September 14, 2018 will proceed with publication as an Open Access article starting on January 13, 2021 in the gold Open Access journal, Journal of Global Information Management (converted to gold Open Access January 1, 2021), and will be distributed under the terms of the Creative Commons Attribution License (<http://creativecommons.org/licenses/by/4.0/>) which permits unrestricted use, distribution, and production in any medium, provided the author of the original work and original publication source are properly credited.

with people. Therefore, m-Health can serve patients both in everyday life and during hospitalization, as well as health care providers during emergency and even in routine visits.

As an emerging market, Bangladesh is experiencing significant advances and development in health care sectors in recent years. The government has developed a Health Management Information System (MIS) department under the Directorate General of Health Services (DGHS). The purpose of this department is to ensure the best use of ICT to build and maintain nationwide health information system of Bangladesh (DGHS, 2014). This works as the backbone of the e-Health service network of Bangladesh and m-Health service is rendered using the national wide mobile phone network. The health professionals provide basic health advices and initial diagnosis when the service recipients' contacts through specialized 24/7 call centers. It has established free tele-consultation with government doctors, SMS services for patient management and communication with staff, etc. These cell phone numbers are circulated among the surrounding community. As such, people residing in the rural areas can be in contact with the health professionals through this network. Moreover, web-camera has been given in each sub-district, district, medical college and post-graduate institute hospitals in Bangladesh. These hospitals, therefore, can give telemedicine services using Skype (free voice over internet provider service and instant messaging client) or any other video conferencing platform. Many mobile phone companies are also providing medical advice and prescriptions to millions of callers in their networks at nominal fees, alleviating some of the access and timeliness related challenges in the provision of healthcare services in Bangladesh (Rashidee, 2013).

However, m-Health service does not yet have a wide coverage in Bangladesh. Across the entire country, m-Health services are being extensively provided in only rural areas, which show that the capital city of Dhaka remains deprived of the availability of such services till today. As such, this paper is focusing on the acceptance, use, future prospect and necessity of m-Health services among the dwellers of Dhaka city in Bangladesh.

For this paper, the unified theory of acceptance and use of technology (UTAUT) model with age and gender as moderating effects has been used. This study employed proposed constructs of system quality (system reliability, system efficiency, system privacy), information quality, interaction quality (responsiveness, assurance, empathy), personal innovativeness, anxiety, perceived credibility, perceived self-efficacy, perceived financial cost, health-care knowledge and trust, to examine the factors that can influence users' intention to use m-Health services in Bangladesh. Moreover, this study has both theoretical and managerial implications. Theoretically, drawing upon relevant literature, this study aims to provide a model that is capable of understanding the determinants behind the future adoption of m-Health services among city-dwellers in Bangladesh. From a managerial perspective, the findings of this research should provide further insights into understanding and managing potential m-Health users, particularly hailing from the capital city of the country. This study can also assist various public and private hospitals in Dhaka city, along with various telecommunication networks to consider the idea of providing m-Health services to the urban people of Bangladesh.

LITERATURE REVIEW

Following globalization, there has been an ever-increasing need for digitalization – as a result of which, different technology-based products and services are being globally offered to the consumers. However, modern-day consumers actively seek information about the technology-based product/service prior to making a purchase decision in order to make the best decision possible (Khatwani and Srivastava, 2015a).

It has been observed that consumers go through five stages in the buying process, namely, need recognition, pre-purchase, evaluation of alternatives, purchase and post-purchase (Khatwani and Srivastava, 2015b). According to Crotts (1999), consumers may search for products/services in the pre-purchase phase based on either their past experiences (internal information) or various attributes of the products/services and characteristics of the users themselves (external information). In case the product/service is technology-based and if the content is sensitive like healthcare provisions, search

for it mostly depends upon individual acceptance and use of information technology according to many literatures.

Initially, researchers were more focused on developing ideas from theories in psychology and sociology rather than using technology acceptance and usage as the basis of their studies. Over time, the focus shifted towards technology acceptance and use, wherein the Technology Acceptance Model (TAM) was widely employed in many past studies like Davis (1989) and Davis et al. (1989). Based on TAM synthesis of prior technology acceptance research, Venkatesh et al. (2003) developed the unified theory of acceptance and use of technology (UTAUT) model. The factors included in UTAUT (performance expectancy, effort expectancy, social influence and facilitating conditions) has been primarily used to predict the behavioral intention to use a technology and technology use in organizational contexts, moderated by individual difference variables like age, gender, experience and voluntariness. In both organizational and non-organizational settings, UTAUT has repeatedly served as a baseline model to study a variety of technologies. However, given the number of technology devices, applications and services that are targeted at consumers in recent times, it became necessary to identify the factors that can influence consumer adoption and use of technologies (Stofega & Llamas, 2009). This led to the introduction of the UTAUT2 model by Venkatesh et al. (2012). In UTAUT2, Venkatesh et al. (2012) adapted the four key constructs (i.e. performance expectancy, effort expectancy, social influence and facilitating conditions) that influence behavioral intention to use a technology and technology use from the original UTAUT model and customized it to fit the consumer context. In addition, Venkatesh et al. (2012) added three new constructs to the UTAUT2 model - hedonic motivation, price value and habit and included only three moderating variables of age, gender and experience to make the model applicable to the consumer use context. Venkatesh et al. (2012) further claimed that the addition of such new constructs in a consumer context can contribute to the expansion of the theoretical horizons of the UTAUT model.

An impressive body of academic research (e.g. DeLone and McLean, 2003; Nelson et al., 2005; Lallmahamood, 2007; Jung, 2008; Lee and Chung, 2009; Lin, 2011; Lau et al., 2013) therefore adapted various forms of quality dimensions in order to investigate users' quality perceptions regarding a technology-based product/service. Kahn et al. (2010), Fox (2011) and Kumar et al. (2013) suggested that information quality can significantly predict users' perception regarding m-Health services if information about healthcare services is complete, accurate and up-to-date. Free et al. (2013) and Nisha et al. (2016) further stated that the presence of such characteristics in healthcare information will ultimately result into the enhancement of information quality. Some latest studies like Sunyaev et al. (2014), Hoque et al. (2015) and James et al. (2015) argued that reliability, efficiency and privacy are other major dimensions of quality that should be inspected in the context of sensitive mobile-based technologies like healthcare services. Moreover, findings by Huang et al. (2015), Washington et al. (2015) and Yin et al. (2016) claimed that factors like responsiveness, assurance and empathy also represent quality dimensions that affects user's loyalty indirectly and directly towards the use of mobile technology like m-Health services.

According to Khatwani and Srivastava (2015b), the consideration of consumer's personal factors by service providers can fully utilize the potential of services provided over internet or mobile channels. As such, personal traits like innovativeness, anxiety, knowledge and self-efficacy have been investigated in the context of m-Health services in this study. Researchers like Evans et al. (2012), Sieverdes et al. (2013) and Maddison et al. (2014) claimed that the judgment of one's ability to use health services over the mobile platform is an important determinant and a causal relationship between perceived self-efficacy and behavioral intention of consumers exists towards m-Health services. Meanwhile, Putzer and Park (2012), West (2012) and Jackson et al. (2013) argued that consumers with innovativeness generally showcase a positive behavior towards the adoption of new technology-based services. Additionally, Gagnon et al. (2015) and Townsend et al. (2015) stated that the probability of consumers seeking m-Health services is dependent on their prior knowledge on such. This implies when knowledge is handy by other means, instead of seeking the service elsewhere consumers prefer

using healthcare services over the mobile platform. However, findings of Brian and Ben-Zeev (2014), Cairney et al. (2014) and Deng et al. (2014) claimed that a certain level of technology anxiety among users can act as a resistance towards m-Health services, forming an unfavorable attitude and less willingness to use such a technology for their healthcare needs.

Some more important driving factors towards the adoption of m-Health services have been identified in literature as the financial cost, trust and credibility related to the use of such services and its providers. Past studies by Tamrat and Kachnowski (2012), Kumar et al. (2013) and Silva et al. (2015) argued that the construct of perceived financial cost has a negative impact upon the behavioral intention of consumers to use m-Health services. In contrast, trust has been found to have a direct, positive effect on usage intentions in various technology-based studies. Researchers like Akter et al. (2013), Deng et al. (2014) and Vedder et al. (2014) investigated trust and revealed a positive relationship between the level of trust in systems of care and their care provider and consumers' use of healthcare services. Along the same line, findings of Boudreaux et al. (2014), Agarwal et al. (2015) and Nisha et al. (2015) relates credibility to the process of generating trust in mobile based technological services like m-Health – thereby, stating that the credibility of the healthcare service provider can create trust among consumers and have an indirect influence upon consumers' use of technology-based health services.

Following the suit, the current study has selected the original UTAUT and UTAUT2 model as a theoretical foundation to develop a proposed research model for the domain of healthcare from the consumers' perspective. Crucial dimensions that can have an impact upon the acceptance and use of m-Health services has been gathered from the existing literature – making this study a thorough and an exhaustive one. Apart from contributions to the literature as a far-reaching study in m-Health, it will assist service providers to comprehend the factors that can influence consumers' behavior so that they can fully utilize the potential of technology-based products and services like m-Health applications.

RESEARCH MODEL AND HYPOTHESES

The proposed research model used to address the influencing factors for healthcare technologies has been presented in Figure 1. In addition, all the variables hypothesized in this study and their likely relationships towards consumer acceptance and use of m-Health services in Bangladesh has been discussed next.

System Quality

System quality is an overall measure of the information processing system itself. The three most significant dimension of system quality are discussed below.

System Reliability

System reliability measures the extent to which a system is dependent over time (Varshney, 2005). It explains the accuracy of the technical functioning of the system and also the truthfulness of service promises (Parasuraman et al., 2005). According to Nelson et al. (2005), it can be defined objectively as the technical availability of the system or the ability of the system to provide error free services. As a result, it can be easily and correctly measured by metrics like uptime, downtime or mean time between failures (Nelson et al., 2005). However, sometimes individual perceptions of reliability can depict a totally different picture from the measured reliability. Thus, often consumers' perception of system reliability plays a vital role in capturing consumers' perceptions of m-Health services (Akter et al., 2010).

System Efficiency

From a consumer perspective, an efficient system is the one that is simple to use, structured properly, and requires minimum information to be input by individual (Parasuraman et al., 2005). It measures

ease of use, ease of access, service processing time, ubiquity, simplicity and structure (Akter et al., 2010). Three very important attributes of system efficiency generally are accessibility, flexibility and response time. Therefore, how quickly consumers can reach the system when needed, how fast the system can be acclimatized to a variety of user needs and changing conditions and how quickly or timely the system responds to requests for information or action – all define system efficiency (Akter et al., 2010). These three attributes usually have a strong influence on performance expectancy of m-Health services as they guide the perceptions of system quality and ultimately affect the usage intention of people. Nelson et al. (2005) and Akter et al. (2010) further claimed that consumers with more positive beliefs about accessibility, flexibility and response time are more willing to use m-Health services.

System Privacy

According to Angst and Agarwal (2009), concern over privacy and security of personal health information is one of the reasons that held consumers from using m-Health services in developing countries. Perceived privacy of consumer can be defined as the users' perception of protection against security threats and control of their personal health care information in an online environment (Lallmahmood, 2007). It measures the degree to which the user believes the system is safe from intrusion and personal information is protected (Akter et al., 2010). As developing countries like Bangladesh are not that much rich in terms of technology, users often object to transmit personal information. However, this objection can reduce with mature technology and secure system which will ultimately affect performance expectancy of m-Health positively.

Hence, this study proposes the following hypotheses from system quality:

H1A: System reliability positively influences performance expectancy of m-Health services.

H1B: System efficiency positively influences performance expectancy of m-Health services.

H1C: System privacy positively influences performance expectancy of m-Health services.

Information Quality

Information quality (IQ) plays a critical role in building user satisfaction and customer loyalty for mobile internet services (Jung, 2008). Lee and Chung (2009) suggested that information quality can significantly predict users' perception regarding the use of mobile based technology in sensitive areas like banking or healthcare. Generally, the three most important indicators of information quality are completeness, accuracy and currency (Masrek et al., 2012). Accuracy has been defined as the extent to which the information is correct, unambiguous, objective and meaningful or believable (Wand and Wang, 1996). On the other hand, completeness refers to the extent to which all possible states relevant to the user population are available in the stored information (Nelson et al., 2005). In order to overcome any ambiguity of completeness, researcher has identified currency of information as another dimension of information quality. According to Nelson et al. (2005), currency can be defined as the degree to which information is up to date, or the degree to which the information precisely reflects the current state of the world. Even Khatwani and Srivastava (2015a) supported the characteristic of updated pace as a way to improve information quality. Together, all these three attributes capture the key elements of information quality and direct users' perception regarding m-Health services. As such, information quality might have a significantly positive effect on performance expectancy, which in turn can impact the behavioral intention of consumers towards m-Health. Thus, the study hypothesizes that:

H2: Information quality positively influences performance expectancy of m-Health services.

Interaction Quality

Lin (2011) claimed that interaction quality in the form of responsiveness, assurance and empathy affects users' loyalty indirectly and directly toward mobile internet technology. All these three factors are therefore discussed below.

Responsiveness

Responsiveness is the most important indicator of interaction quality (Lau et al., 2013). It can be defined as the willingness to help users and to provide prompt services (Akter et al., 2010). It can further be explained by the providers' ability to understand the users' problems and to provide precise services. Lau et al. (2013) found positive relationship between responsiveness and consumer loyalty. Based on this evidence, this study used responsiveness as a factor that will guide consumers regarding m-Health service adoption.

Assurance

Assurance measures knowledge, competency and courtesy of the provider that generate users' trust and confidence in the system (Akter et al., 2010). It is the second most important factor of interaction quality that inspires consumer loyalty (Lau et al., 2013). The service provider's ability to provide their promised and accurate services and their tendency of keeping commitments can only assure users regarding the adoption of mobile based technology. As past evidences from Lin (2011) and Lau et al. (2013) found positive relationship between assurance and consumers' acceptance of mobile technology, it has been perceived as an influencing factor in the context of m-Health in this study.

Empathy

The final dimension of interaction quality is empathy that refers to the understanding ability of the users' needs and ability to provide personalized attention (Akter et al., 2010). Consumers always appreciate a friendly and considerate environment. Hence, if the service provider shows genuine interest, enthusiasm and seriousness toward the users' needs, it will automatically lead consumers towards usage of that service. In fact, Lau et al. (2013) found the highest correlation between empathy and customer satisfaction. This study thus proposes that empathy can positively influence performance expectancy, which in turn can lead to the behavioral intention of consumers towards m-Health.

This study hypothesizes the following from interaction quality:

H3A: Responsiveness positively influences performance expectancy of m-Health services.

H3B: Assurance positively influences performance expectancy of m-Health services.

H3C: Empathy positively influences performance expectancy of m-Health services.

Personal Innovativeness

Innovativeness is the willingness to adopt an innovative technology or in other words, it is the degree of interest in trying a new thing, new concept or an innovative product or service (Rogers, 1995). As per Khatwani and Srivastava (2015a), it is the interest in technological products that defines personal innovativeness. It has been tested and proved as a significant construct that affects technology usage intention very often by researchers like Agarwal and Prasad (1998), Hung et al. (2003) and Yang (2005). According to innovation diffusion theory (IDT), people react differently towards a new technology due to differences in personal innovativeness, which is an inclined tendency toward adopting an innovation (Rogers, 2005). This theory also stated a set of innovation attributes that may affect adoption decisions like relative advantage, ease of use, complexity, compatibility, observability and trialability (Ami-Narh and Williams, 2012). Many empirical evidences also proved that relative advantage and ease of use are the key constructs of performance expectancy and effort expectancy

respectively in the UTAUT model (Venkatesh et al., 2003). Since Rai et al. (2013) showed positive relationship between personal innovativeness and adoption of m-Health technology, in order to emphasize this relationship further, this study hypothesizes that:

H4A: Personal innovativeness positively influences performance expectancy of m-Health services.

H4B: Personal innovativeness positively influences effort expectancy of m-Health services.

Anxiety

According to Kohnke et al. (2014), anxiety can be defined as the participants' self-reported hesitation while adopting a new technology. Venkatesh et al. (2003) showed anxiety as an independent and indirect determinant of intention of adopting a technology. However, Akter et al. (2013), Kohnke et al. (2014) and Silva et al. (2015) stated that when a patient forms a negative attitude towards using an internet-based technology to solve his problems, he views it as a source of anxiety and as a result, the patient has low intention to use that technology. In developing countries like Bangladesh, where literacy rate is low people might perceive a technology like m-Health to be complex and feel anxious regarding the use of it. As complexity is the degree to which a system is perceived as relatively difficult to understand and use, Venkatesh et al. (2003) stated it as one of the constructs of effort expectancy which shapes behavioral intention for the use of a technology. Therefore, the following hypothesis has been conceived for this study:

H5: Anxiety negatively influences effort expectancy of m-Health services.

Performance Expectancy

Performance expectancy generally depicts a users' view of the usefulness of adopting a technology. According to Venkatesh et al. (2003), performance expectancy is particularly identical to perceived usefulness factor of the original TAM model, which claimed that when a user perceives a technology useful, the likelihood of adopting that technology increases. Moreover, Sun et al. (2013) claimed that in the context of m-Health services, the usefulness can only be captured by the extent to which it can help users to solve their health-related issues. If users believe that using m-Health services can help them to solve their problems, they are more likely to adopt this technology (Nisha et al., 2016). Hence, the hypothesis is:

H6: Performance expectancy significantly affects individual intention to use m-Health services.

Effort Expectancy

Effort expectancy is considered to be directly related with the ease of using a particular technology (Phichitchaisopa and Naenna, 2013). The effort-oriented constructs act as more significant factors during the early stages of adopting a new technology. Khatwani and Srivastava (2015a) stated that to promote the use of a particular technology, design and structure of the technological service needs to be user-friendly. This is because only mobile and internet technologies can fundamentally differentiate an electronic service from the conventional ones. Several studies like Moores (2012) and Sun et al. (2013) claimed that user friendliness, perceived ease of use or effort expectancy has considerable impacts on attitude towards the adoption of m-Health or any other healthcare related technology. As a result, the following hypothesis is proposed:

H7: Effort expectancy significantly affects individual intention to use m-Health services.

Social Influence

Social influence refers to the degree to which an individual perceives that important others believe he or she should use the new system or technology (Venkatesh et al., 2003). According to Khatwani and Srivastava (2015b), one of the prominent external information search channels for technology-related service users tends to be personal like advice from friends or relatives using social media channels. The idea behind social influence is that even though an individual may not be in favour of adopting a new technology, they intend to use it as he/she believes it will enhance his/her image among his/her family and peers (Venkatesh and Davis, 2000). Many studies like Jung (2008) and Sun et al. (2013) indicated a positive relationship between social influence and behavioural intention towards m-Health technology. Thus, the proposed hypothesis is:

H8: Social influence significantly affects individual intention to use m-Health services.

Facilitating Conditions

Facilitating conditions refer to the resources and technical infrastructure that a user believes exists to support the adoption of a particular technology. In other words, facilitating conditions indicates the prospective conditions that may restrain or facilitate adopting a technology (Sun et al., 2013). According to Khatwani and Srivastava (2015a), unique characteristics like access speed, access scope and interactive assistance associated with mobile and internet significantly impacts the usage of a technological service. Past studies by Venkatesh and Zhang (2010) and Venkatesh et al. (2012) claimed that a consumer with a lower level of facilitating conditions may have a lower intention to use a particular technology. Moreover, researchers like Boontarig et al. (2012), Phichitchaisopa and Naenna (2013) and Sun et al. (2013) showed that there is a positive significant relationship between facilitating conditions and health care technologies. Based on these findings, this study hypothesizes that:

H9: Facilitating conditions significantly affects individual intention to use m-Health services.

Perceived Self-Efficacy

Self-efficacy refers to the users' judgment of their ability to perform a particular behaviour (Compeau and Higgins, 1995). The concept of self-efficacy is identical to perceived behavioral control and according to Sun et al. (2013), perceived behavioral control in the context of m-Health services can be defined as the users' ability to learn and use mobile health services. If a user is confident enough regarding his ability to adopt a technology like m-Health, he/she is more likely to adopt that technology. In fact, Wu et al. (2007), Burner et al. (2013) and Sun et al. (2013) empirically proved that self-efficacy is a determinant of the intention and usage behavior of m-Health services. Accordingly, the following hypothesis has been conceived:

H10: Perceived self-efficacy significantly affects individual intention to use m-Health services.

Perceived Financial Cost

Even though researchers generally investigate user adoption of a technology from psychological and sociological theories, it has been proved by Yu (2012) and Sun et al. (2013) that technology acceptance is influenced by economic factors as well. Financial cost is thus a very crucial predictor of the acceptance behavior of technological services as it refers to the cost or resources (money) associated with the learning and using of that technology. According to Yang (2009) and Deglise et al. (2012), if a user needs to spend considerable amount of money to pay for the services to learn or to use the technology, he/she will be unwilling to use it, demonstrating a negative relationship between

financial cost and behavioral intention. Moreover, Khatwani and Srivastava (2015a) stated that mobile technology helps organizations in reducing cost, which further lowers the financial burden on users resulting in more usage of that technological service. Hence, the hypothesis is:

H11: Perceived financial cost significantly affects individual intention to use m-Health services.

Health Care Knowledge

Khatwani and Srivastava (2015a) stated that product knowledge is very crucial in influencing the adoption of technological products. Therefore, users' knowledge regarding healthcare can act as an important predictor of m-Health adoption. This is relatively a less investigated construct and was developed to measure the users' extent of knowledge and understanding of personal health problems (Wilson and Lankton, 2004). Given all the resources and necessary infrastructure, people may tend to use internet-based health technologies to gain information regarding a health issue and increase their knowledge. This indicates that users who feel that they have relatively little knowledge about healthcare are more likely to adopt healthcare technologies. However, when Domínguez-Mayo et al. (2015) and Hasanain et al. (2015) investigated this construct against the backdrop of e-Health technology they found it insignificant as a predictor of behavioral intention. To focus on this relationship further, this study hypothesizes that:

H12: Health care knowledge significantly affects individual intention to use m-Health services.

Perceived Credibility

Perceived credibility can be defined as the extent to which an individual perceives the m-Health service provider to have the required expertise to perform effectively and reliably. In the context of health care, the issue of the credibility of the service provider is imperative. It is even more factual for online environment, where uncertainty regarding the service provider exists. If a user believes that the m-Health service provider is not credible, he/she will not trust the service and as a result, there will be unwillingness to adopt the technology. Several researchers like Koenig-Lewis et al. (2010), Dasgupta et al. (2011) and Yu (2012) investigated this construct and found significant positive relationship between credibility and trust, followed by a resulting positive effect on technology adoption. Moreover, Korp (2006) and Jung (2008) supported the claim by providing evidence that high perceived credibility generate trust for internet-based health services, which in turn affects the behavioural intention of adopting such technologies. In order to completely ascertain this relationship, this study proposes that:

H13: Perceived credibility positively influences individual trust for m-Health services.

Trust

As mentioned above, perceived credibility plays an important role in creating trust and some researchers like Watzdorf et al. (2010) further claimed that past experiences with a technology have the biggest impact on trust. Khatwani and Srivastava (2015b) stated that neutral sources like discussion forums and information blogs and experiential sources like online demo of technological products through review websites can contribute to the creation of trust. According to Rousseau et al. (1998), trust can be defined as a psychological state comprising the intentions to accept vulnerability based on positive expectations of the behaviour of another. It is a social and personal factor that has been investigated by Lin (2011) and El-Wajeeh et al. (2014) in various dimensions such as personality-based trust, knowledge-based trust, etc. Prior empirical studies like Mohamed et al. (2011) and El-Wajeeh et

al. (2014) have particularly employed the construct of trust in the context of internet-based health services and found that trust has a direct significant influence on behavioural intention to use both e-health and m-Health services. Thus, the following hypothesis has been conceived:

H14: Trust significantly affects individual intention to use m-Health services.

Behavioral Intention

Behavioral intention, which refers to the intention to use a system, is the major determinant of the actual behaviour. Researchers like Venkatesh and Zhang (2010) and Yu (2012) have repeatedly emphasized the strength of the construct of behavioral intention on usage behaviour. These past studies claim that individual behavior is predictable and can be influenced by individual intention that, in turn, can have a significant influence on technology usage. Moreover, Venkatesh and Davis (2000) found significant positive correlation of behavioral intention and actual use. In the context of m-Health services, Jung (2008) and Sun et al. (2013) investigated and empirically proved that behavioural or adoption intention of the technology positively affects its usage. Following the lead, this study next hypothesizes that:

H15: Behavioral intention significantly affects individual behavior of using m-Health services.

Moderators

Moderators are demographical characteristics or other situational variables that have a profound impact on user adoption (Jung, 2008). Since this study is not a longitudinal study, only age and gender has been used in this study as moderators to investigate the effects of the proposed research structure on the behavioral intention to adopt m-Health services and individual behavior of using m-Health.

Moderator Effects – Age

Past empirical studies like Venkatesh et al. (2003) and Gilbert et al. (2004) claimed that age has a strong moderating impact on technology adoption. According to Jung (2008), younger generation is more eager to adopt a technology like m-Health services than older generation, since younger people tend to be more tech-savvy, they can adopt any technology quickly. In addition, due to high perceived accessibility, credibility, personal innovativeness and compatibility all internet-based health technologies go well with the life style of young people, which in turn leads them to accept the technology. However, Lee and Rho (2013) argue that middle-aged people display more enthusiasm towards adopting m-Health technology than the younger people. As a result of this conflicting evidence, the following hypotheses are proposed:

H16: Influence of performance expectancy on individual intention will be moderated by age.

H17: Influence of effort expectancy on individual intention will be moderated by age.

H18: Influence of social influence on individual intention will be moderated by age.

H19: Influence of facilitating conditions on individual intention will be moderated by age.

H20: Influence of perceived self-efficacy on individual intention will be moderated by age.

H21: Influence of perceived financial cost on individual intention will be moderated by age.

H22: Influence of health care knowledge on individual intention will be moderated by age.

H23: Influence of trust on individual intention will be moderated by age.

Moderator Effects - Gender

Several researchers like Laukkanen and Pasanen (2008) and Cruz et al. (2010) claimed that women are naturally risk averse and passive users of technology which makes them less willing to spend more

effort associated with adopting a new system. On the other hand, these empirical studies proved men being more concerned about the cost related to a particular technology. Venkatesh and Morris (2000) found performance expectancy to be more important construct for men while constructs that relate to technical abilities such as effort expectancy appeared to be more salient for women. Venkatesh et al. (2003) further claimed that social influences act as a stronger predictor of technology adoption for women than men. However, Jung (2008) and Lee and Rho (2013) claimed that women are usually more concerned about health-related issues, which in turn makes them to adopt internet-based health technologies. Thus, this study hypothesizes that:

H24: Influence of performance expectancy on individual intention will be moderated by gender.

H25: Influence of effort expectancy on individual intention will be moderated by gender.

H26: Influence of social influence on individual intention will be moderated by gender.

H27: Influence of facilitating conditions on individual intention will be moderated by gender.

H28: Influence of perceived self-efficacy on individual intention will be moderated by gender.

H29: Influence of perceived financial cost on individual intention will be moderated by gender.

H30: Influence of health care knowledge on individual intention will be moderated by gender.

H31: Influence of trust on individual intention will be moderated by gender.

RESEARCH METHOD

Data Collection

The predominant existence of m-Health services in the rural areas has inadvertently deprived urban people of the use of such services. In addition, the absence of city hospitals as the provider of m-Health services has made it imperative to examine the acceptance and use of m-Health services among the city dwellers of Bangladesh. As such, the population selected for this study only represents urban people who are currently exposed to the use of mobile phones and can thereby avail m-Health services in the future.

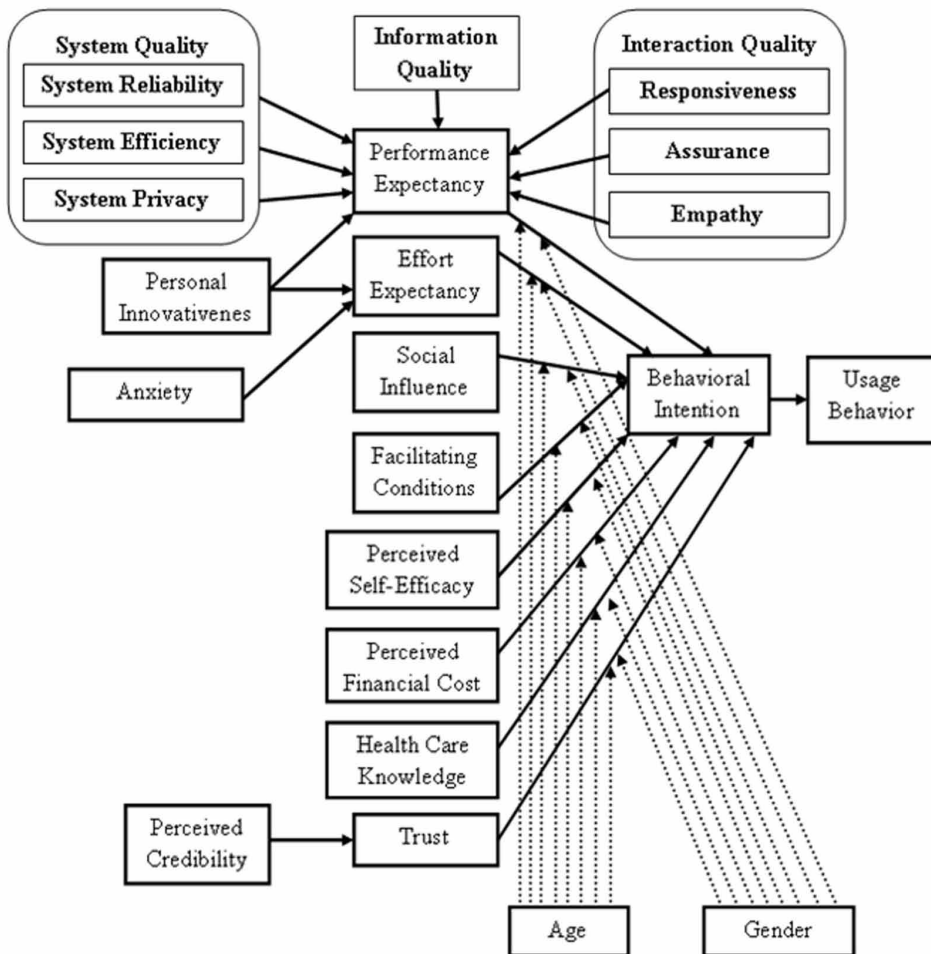
Data for this study is collected by conducting a survey through paper-based questionnaires on a sample of 1000 respondents in the capital city of Bangladesh – Dhaka. By using probability sampling and a stratified random sampling method, respondents are then selected for the sample. The use of this particular sampling method allows us to avoid biasness in data and provide equal opportunity for all city dwellers who can be the potential users of m-Health services in Bangladesh.

Measurement

All the items used to measure the research variables of the survey are adapted from previous studies on information and technological advancements, e-health services and m-Health services - with minor changes in wording to tailor them to the context of Bangladesh. This ensures the content validity of the questionnaire used to assess each constructs depicted in Figure 1.

The quantitative survey contains 62 statements in order to evaluate the eight constructs of the UTAUT model and the eleven new constructs proposed for the model, as listed in **Table 1**. The scales for the UTAUT constructs (performance expectancy, effort expectancy, social influence, facilitating conditions, perceived self-efficacy, perceived financial cost, perceived credibility and behavioral intention) are adapted from Jung (2008), Venkatesh and Zhang (2010), and Sun et al. (2013). The scales for system quality (reliability, efficiency and privacy), information quality and interaction quality (responsiveness, assurance and empathy) are drawn from Lee and Chung (2009), Lin (2011), Lau et al. (2013) and Nisha et al. (2016). On the other hand, the items used to assess personal innovativeness, anxiety, trust and health care knowledge are based on Wu et al. (2011), Nisha et al. (2015) and Nisha

Figure 1. The Proposed Research Structure



et al. (2016). All these items are measured using a five-point Likert scale, ranging from “strongly disagree” to “strongly agree”.

The questionnaire includes two demographic questions of gender and age as well. While age is measured in years, gender is coded as 1 or 2 dummy variable - where 2 represent the female respondents. After a four-week survey, 927 completed and usable responses are obtained from the structured questionnaires. Table 2 represents the demographic information of respondents in terms of gender and age.

DATA ANALYSIS AND RESULTS

The research model is tested using the structural equation modeling (SEM) facilitates of SmartPLS (version 2.0). The method of partial least squares (PLS) is mainly chosen to conduct this analysis since a number of interaction terms are included in the research model and PLS is capable of testing

Table 1. Constructs and Corresponding Items

Constructs	Corresponding Items
System Reliability	(SR1) I believe m-Health services operate reliably (SR2) I believe m-Health services perform reliably (SR3) I believe the operation of m-Health services is dependable
System Efficiency	(SE1) I feel m-Health services make health information easy to access (SE2) I feel m-Health services provide health information in a timely fashion (SE3) I feel m-Health takes too long to respond to my healthcare problems
System Privacy	(SP1) I trust the ability of m-Health services to protect my privacy (SP2) I feel safe when I release health information to m-Health services (SP3) I feel matters on security has no influence in using m-Health services
Information Quality	(IQ1) I believe m-Health services provide complete information (IQ2) I believe m-Health services provide up-to-date information (IQ3) I believe m-Health services provide relevant information
Responsiveness	(R1) I think m-Health provides precise healthcare services (R2) I think m-Health has the ability to understand my healthcare needs (R3) I think m-Health services are helpful
Assurance	(As1) I think m-Health provides healthcare services as promised (As2) I think m-Health provides accurate healthcare services (As3) I think m-Health services will keep their commitments
Empathy	(E1) I think m-Health has the knowledge to solve my healthcare problems (E2) I think m-Health has the enthusiasm to understand my healthcare needs (E3) I think m-Health services will put my healthcare needs in the first place
Personal Innovativeness	(PI1) I am curious about new health technologies (PI2) I am usually among the first to try new health technologies (PI3) I like to experiment with new health technologies (PI4) I like to keep updated with new health technologies
Anxiety	(A1) I feel apprehensive about using new health technologies (A2) I'm scared of information loss due to mistakes in new health technologies (A3) I hesitate to use new health technologies for fear of making mistakes (A4) I feel intimidated to use new health technologies
Performance Expectancy	(PE1) Using m-Health services will improve my life quality (PE2) Using m-Health services will make my life more convenient (PE3) Using m-Health services will make me more effective in my life (PE4) Overall, I find m-Health services to be useful in my life
Effort Expectancy	(EE1) Learning to use m-Health services is easy for me (EE2) Becoming skillful at using m-Health services is easy for me (EE3) Interaction with m-Health services is easy for me (EE4) Overall, I think m-Health services are easy to use
Social Influence	(SI1) People who are important to me think that I should use m-Health services (SI2) People who are familiar with me think that I should use m-Health services (SI3) People who influence me think that I should use m-Health services (SI4) Most people surrounding me use m-Health services
Facilitating Conditions	(FC1) Using m-Health services suits my living environment (FC2) Using m-Health services fits into my working style (FC3) Using m-Health services is compatible with my life (FC4) Help is available if I have problems in using m-Health services
Perceived Self-Efficacy	(PSE1) It is easy for me to use m-Health services (PSE2) I have the capability to use m-Health services (PSE3) I am able to use m-Health services without much effort
Perceived Financial Cost	(PFC1) The cost of using m-Health services is higher than other health channels (PFC2) The internet charges required to use m-Health services are expensive (PFC3) The mobile devices required to use m-Health services are expensive (PFC4) Using m-Health services can be a cost burden to me
Health Care Knowledge	(HCK1) I am very knowledgeable regarding care for my health problems (HCK2) I understand my health problems and how to care for them
Perceived Credibility	(PC1) I believe m-Health services will keep my information confidential (PC2) I believe that using m-Health services will be secure (PC3) I believe that using m-Health services will be safe
Trust	(T1) I believe m-Health services to be trustworthy (T2) I believe m-Health services to be credible
Behavioral Intention	(BI1) I prefer to use m-Health services (BI2) I intend to use m-Health services (BI3) I plan to use m-Health services

Table 2. Demographic Profile of Respondents

Demographics	Frequency	Percentage (%)
Gender		
Male	546	58.9
Female	381	41.1
Age		
20 or below	158	17.0
21 – 30	476	51.3
31 – 40	145	15.6
41-50	94	10.1
Above 50	54	5.8

these effects (Chin et al., 2003). As such, the measurement model is examined first to assess the reliability and validity of the constructs and then, the structural model is analyzed to examine the relationships hypothesized in the research model.

Measurement Model

To test the validity of the measurement model, a conformity analysis test has been conducted which includes both convergent validity and discriminant validity (Campbell and Fiske, 1959). Convergent validity measures whether the items effectively reflect their respective constructs, whereas discriminant validity shows whether the constructs are statistically different from each other.

The convergent validity has been checked through factor loadings, average variance extracted (AVE) and composite reliability (CR) of the items and constructs. The values for the measurement model are given below in Table 3. For this study, the minimum cut-off level for the values of item loadings has been considered as 0.70, as recommended by Nunnally and Bernstein (1994). For AVE, 0.50 has been considered as the minimum cut-off level following Fornell and Larcker (1981). Results indicate that AVE values of the constructs of this study is well above 0.50 in all cases and greater than each square correlation. For CR, 0.70 has been considered as the minimum cut-off value, as suggested by Chin et al. (2003). Since the composite reliabilities of the constructs range between 0.731 and 1.000, it suggests internal consistency for the proposed model. Evaluation of all these values suggest that the items surveyed under the proposed model of this study effectively reflect their respective constructs and thereby poses a satisfactory level of internal consistency.

In order to test the discriminant validity, two measures have been adopted: Fornell-Larcker criterion and the cross-loadings. Under the Fornell-Larcker criterion, it is suggested that that square root of AVE of each construct should be greater than its highest latent variable correlation (Fornell and Larcker, 1981). Table 4 proves that the constructs used in this study satisfy the Fornell-Larcker criterion, as represented by the square root of AVE of each construct of latent variables and all latent variable correlations. Observations suggest that the square root of AVE of each construct stands highest among the values of their latent variable coefficients. This further suggests that the result of the Fornell-Larcker criterion is satisfactory and hence the model poses good discriminant validity. Moreover, the internal consistency reliabilities (ICRs) of multi-item scales modeled with reflective indicators is 0.75 or greater, suggesting adequate reliability.

The second measure that has been adopted for measuring discriminant validity is the cross-loading matrix. In this case, it is expected that the items demonstrate higher loadings in their respective constructs (Chin, 1998). In Table 5, the cross loading matrix is visible and from there it can be observed that the items have higher loading value in their respective constructs - which suggests

the satisfaction of discriminant validity of this property. The pattern of loadings and cross-loadings also support internal consistency and discriminant validity, with some exceptions: one item from each construct of information quality, empathy (interaction quality), personal innovativeness, social influence, facilitating conditions, perceived financial cost, health care knowledge, two items from system reliability (system quality) and system efficiency (system quality) and three items from anxiety are deleted due to their low loadings and high cross-loadings.

Structural Model

The bootstrapping method from PLS path modeling approach has been used in this study to examine the structural paths of the proposed research model. For the purpose of analysis, the confidence intervals and R^2 value is employed to validate the structural paths of the conceptual model.

Prior studies suggest that it is going to be more vital to report the confidence intervals rather than just reporting the significance of the constructs (Henseler et al., 2009). Hence, the t-statistics are calculated using the path coefficients of the constructs and their bootstrapped standard errors, as presented in Table 6.

Among the three constructs of system quality, system reliability (0.240, $p < 0.05$) and system privacy (0.120, $p < 0.05$) shows significant and positive path towards performance expectancy, while system efficiency (0.084, $p > 0.05$) reports an insignificant path. The factor of information quality (0.100, $p < 0.05$) also displays significant and positive path towards performance expectancy. On the other hand, responsiveness (0.135, $p < 0.05$) and empathy (0.072, $p < 0.05$) under interaction quality has significant and positive path towards performance expectancy, but assurance (0.070, $p > 0.05$) shows an insignificant path.

The construct of personal innovativeness has an insignificant path towards both performance expectancy (0.069, $p > 0.05$) and effort expectancy (0.419, $p > 0.05$). Also, anxiety (0.034, $p > 0.05$) shows an insignificant path towards effort expectancy. Along the same line, the factor of perceived credibility (0.258, $p > 0.05$) reports an insignificant path towards the construct of trust in the model.

Among other factors, facilitating conditions (0.235, $p < 0.05$), trust (0.199, $p < 0.05$), effort expectancy (0.169, $p < 0.05$) and performance expectancy (0.155, $p < 0.05$) shows significant and positive paths to the behavioral intention of using m-Health services, in their order of influencing strength. However, the constructs of perceived self-efficacy (0.247, $p > 0.05$), social influence (0.134, $p > 0.05$), health care knowledge (-0.024, $p > 0.05$) and perceived financial cost (-0.066, $p > 0.05$) reports an insignificant path towards the individual behavior of using m-Health services.

Therefore, all hypotheses (except H1B, H3B, H4A, H4B, H5, H8, H10, H11, H12 and H13) dealing with behavioral intention to use m-Health services are supported. Subsequently, the hypothesized relationship between behavioral intention and usage (0.251, $p < 0.05$) is found to be statistically significant, thereby supporting hypothesis H15.

Furthermore, the nomological validity of the proposed model of this study is explained with the R^2 (coefficient of determination) values of all endogenous latent variables. An example of the only endogenous latent variable here is behavioral intention (BI). Henseler et al. (2009) suggests that in order to be acceptable, it is important that the R^2 value is substantial when an endogenous latent variable depends on several exogenous latent variables. The R^2 value for BI is 0.66, which is substantial following Chin (1998). This means that the conceptual model of this study explains 66% of the variance of the behavioral intention to adopt m-Health services and this result is quite significant. Hence, it can be stated that the proposed model is nomologically valid and so is the structural model results of this study. The path coefficients and significance levels in the structural model are also presented in Figure 2.

Moderator Effects

The PLS results of the moderating effects of age and gender on the eight constructs toward behavioral intention are shown in **Table 7**. Results indicate that gender significantly moderates the effect of perceived financial cost, trust and effort expectancy to behavioral intention of using m-Health services.

Table 3. Factor Loadings, Composite Reliability and AVEs

Constructs	Items	Factor Loadings	Composite Reliability	AVE
System Reliability	SR1	1.000	1.000	1.000
System Efficiency	SE1	1.000	1.000	1.000
System Privacy	SP1	0.755	0.789	0.555
	SP2	0.731		
	SP3	0.749		
Information Quality	IQ1	0.908	0.887	0.797
	IQ2	0.876		
Responsiveness	R1	0.801	0.844	0.643
	R2	0.858		
	R3	0.743		
Assurance	As1	0.825	0.881	0.711
	As2	0.849		
	As3	0.855		
Empathy	E2	0.833	0.875	0.778
	E3	0.928		
Personal Innovativeness	PI1	0.853	0.876	0.702
	PI3	0.825		
	PI4	0.835		
Anxiety	A1	1.000	1.000	1.000
Performance Expectancy	PE1	0.807	0.889	0.668
	PE2	0.847		
	PE3	0.850		
	PE4	0.761		
Effort Expectancy	EE1	0.822	0.895	0.680
	EE2	0.834		
	EE3	0.840		
	EE4	0.802		
Social Influence	SI1	0.867	0.891	0.732
	SI2	0.876		
	SI3	0.823		
Facilitating Conditions	FC1	0.776	0.864	0.680
	FC2	0.877		
	FC3	0.818		
Perceived Self-Efficacy	PSE1	0.790	0.860	0.672
	PSE2	0.835		
	PSE3	0.833		
Perceived Financial Cost	PFC2	0.889	0.842	0.642
	PFC3	0.764		
	PFC4	0.743		
Health Care Knowledge	HCK2	1.000	1.000	1.000
Perceived Credibility	PC1	0.806	0.881	0.712
	PC2	0.882		
	PC3	0.841		
Trust	T1	0.915	0.815	0.691
	T2	0.737		
Behavioral Intention	BI1	0.868	0.891	0.731
	BI2	0.873		
	BI3	0.823		

Table 4. Measurement Model Estimations

	ICRs	A	As	BI	E	EE	FC	HCK	IQ	PC	PE	PFC	PI	PSE	R	SE	SI	SP	SR	T
A	1.0	Single-Item Construct																		
As	0.8	0.2	0.8																	
BI	0.8	0.2	0.3	0.9																
E	0.8	0.1	0.1	0.0	0.9															
EE	0.8	0.2	0.3	0.5	0.0	0.8														
FC	0.8	0.2	0.3	0.5	0.0	0.4	0.8													
HCK	1.0	0.2	0.0	0.1	0.0	0.1	0.1	Single-Item Construct												
IQ	0.8	0.2	0.3	0.5	0.0	0.4	0.8	0.1	0.9											
PC	0.8	0.2	0.3	0.4	-0.1	0.8	0.4	0.1	0.4	0.8										
PE	0.8	0.2	0.3	0.4	0.0	0.6	0.4	0.1	0.4	0.5	0.8									
PFC	0.8	0.1	0.1	0.0	0.8	-0.1	0.0	0.1	0.0	-0.1	0.0	0.8								
PI	0.8	0.4	0.3	0.5	0.0	0.4	0.3	0.1	0.3	0.4	0.4	0.0	0.8							
PSE	0.8	0.2	0.2	0.4	0.1	0.2	0.3	0.2	0.3	0.2	0.3	0.1	0.3	0.8						
R	0.8	0.2	0.2	0.4	0.1	0.3	0.3	0.1	0.3	0.3	0.3	0.1	0.3	0.7	0.8					
SE	1.0	0.2	0.8	0.2	0.1	0.3	0.3	0.1	0.3	0.3	0.3	0.1	0.2	0.2	0.2	Single-Item Construct				
SI	0.8	0.3	0.3	0.4	0.1	0.4	0.3	0.2	0.3	0.4	0.3	0.1	0.3	0.3	0.2	0.2	0.9			
SP	0.8	0.3	0.3	0.5	0.1	0.4	0.7	0.2	0.7	0.4	0.4	0.1	0.4	0.3	0.3	0.3	0.7	0.7		
SR	1.0	0.3	0.2	0.4	0.0	0.4	0.3	0.1	0.3	0.4	0.4	0.0	0.8	0.2	0.3	0.2	0.2	0.3	Single-Item Construct	
T	0.8	0.3	0.3	0.3	0.1	0.3	0.3	0.2	0.3	0.3	0.2	0.1	0.3	0.2	0.2	0.2	0.8	0.7	0.2	0.8

Notes:

1. A (Anxiety); As (Assurance); BI (Behavioral Intention); E (Empathy); EE (Effort Expectancy); FC (Facilitating Conditions); HCK (Health Care Knowledge); IQ (Information Quality); PC (Perceived Credibility); PE (Performance Expectancy); PFC (Perceived Financial Cost); PI (Personal Innovativeness); PSE (Perceived Self-Efficacy); R (Responsiveness); SE (System Efficiency); SI (Social Influence); SP (System Privacy); SR (System Reliability); T (Trust).
2. Diagonal elements represent the AVEs, while off-diagonal elements represent the square correlations.

Analysis reveals that male respondents perceive more effort expectancy in using m-Health services and are usually more concerned about the perceived financial cost than the female respondents. However, the trust factor is more crucial for the female respondents than the male counterparts with regard to m-Health services. On the other hand, the moderating effect of age significantly reports for the constructs of effort expectancy, facilitating conditions, performance expectancy and social influence towards behavioral intention. Further analysis reveals that the construct of effort expectancy plays an important role for respondents aged between 41-50 years, while facilitating conditions and performance expectancy are more salient to respondents aged between 31-40 years. However, the construct of social influence tends to have more impact on respondents aged between 21-30 years.

FINDINGS AND IMPLICATIONS

This study has revealed quite a few understandings on the back stage possibilities of the potential usage of m-Health services among the urban population of Bangladesh. The inclined reasons behind the findings are quite obvious and most of such are shaped by the local culture and infrastructure of the country.

Facilitating conditions is found as the strongest direct determinant in influencing respondents' behavioral intention of m-Health services. This finding is consistent to Phichitchaisopa and Naenna (2013), Sun et al. (2013) and Nisha et al. (2015). The penetration of mobile phones is a comparatively new concept in Bangladesh and particularly, when such devices are being used as a platform of commuting other errands such as receiving instant health care advices, ensuring facilitating conditions has a strong role to play. Therefore, the first business implication is that, beyond offering ease-of-use and useful m-Health services, providers can emphasize on the compatibility between the offered

Table 5. Cross Loading Matrix

	A	As	BI	E	EE	FC	HCK	IQ	PC	PE	PFC	PI	PSE	R	SE	SI	SP	SR	T
A1	1.00	0.26	-0.01	0.35	0.19	0.15	0.24	0.32	0.16	0.19	0.11	0.38	0.17	0.29	0.23	0.25	0.26	0.35	0.17
As1	0.20	0.83	0.30	0.17	0.30	0.19	0.21	0.18	0.31	0.39	-0.08	0.43	0.40	0.34	0.35	0.30	0.27	0.19	0.30
As2	0.23	0.85	0.36	0.19	0.27	0.17	0.24	0.28	0.28	0.39	0.00	0.40	0.35	0.32	0.32	0.29	0.27	0.15	0.19
As3	0.26	0.86	0.24	0.11	0.47	0.17	0.35	0.30	0.25	0.36	-0.04	0.35	0.30	0.27	0.28	0.23	0.26	0.24	0.21
BI1	0.32	0.32	0.87	0.14	0.46	0.18	0.37	0.30	0.28	0.53	-0.01	0.34	0.19	0.23	0.30	0.26	0.30	0.32	0.18
BI2	0.27	0.28	0.87	0.23	0.47	0.15	0.37	0.34	0.28	0.45	-0.05	0.33	0.22	0.26	0.20	0.24	0.21	0.29	0.26
BI3	0.23	0.30	0.82	0.25	0.48	0.11	0.37	0.34	0.31	0.43	-0.01	0.37	0.19	0.29	0.02	0.06	0.09	0.27	0.25
E2	0.26	0.20	0.19	0.83	-0.04	0.11	-0.05	-0.03	0.31	0.48	-0.11	0.38	0.18	0.35	0.26	0.30	0.27	0.15	0.37
E3	0.29	0.02	0.22	0.93	-0.03	0.07	-0.02	0.04	0.24	0.31	0.09	0.23	0.17	0.21	0.16	0.19	0.11	0.38	0.17
EE1	0.47	0.17	0.35	0.53	0.82	0.20	0.23	0.26	0.30	0.35	0.00	0.30	0.24	0.27	0.31	0.39	-0.08	0.43	0.40
EE2	0.46	0.18	0.37	0.45	0.83	0.09	0.26	0.24	0.32	0.31	-0.04	0.30	0.22	0.26	0.28	0.39	0.00	0.40	0.35
EE3	0.47	0.15	0.37	0.31	0.84	0.14	0.24	0.47	0.30	0.25	0.17	0.33	0.10	0.34	0.25	0.36	-0.04	0.35	0.30
EE4	0.48	0.11	0.37	0.35	0.80	0.23	0.30	0.46	0.30	0.24	0.40	0.40	0.17	0.41	0.28	0.53	-0.01	0.34	0.19
FC1	0.35	0.00	0.30	0.24	0.27	0.78	0.31	0.47	0.34	0.30	0.35	0.38	0.21	0.41	0.28	0.45	-0.05	0.33	0.22
FC2	0.31	-0.04	0.30	0.22	0.26	0.88	0.14	0.48	0.34	0.31	0.30	0.29	0.11	0.30	0.29	0.25	0.30	0.17	0.29
FC3	0.28	0.07	0.28	0.21	0.33	0.82	0.07	0.17	0.20	0.10	0.19	0.32	0.10	0.26	0.27	0.26	0.27	0.40	0.34
HCK2	0.25	0.04	0.22	0.17	0.26	0.27	1.00	0.20	0.22	0.09	0.22	0.27	0.15	0.24	0.39	0.00	0.40	0.35	0.32
IQ1	0.24	0.09	0.22	0.15	0.24	-0.02	-0.03	0.91	0.06	-0.10	0.19	0.27	0.17	0.24	0.36	-0.04	0.35	0.30	0.27
IQ2	0.29	0.11	0.23	0.18	0.24	-0.03	-0.07	0.88	0.09	-0.07	0.18	0.47	0.17	0.35	0.53	-0.01	0.34	0.19	0.23
PC1	0.19	0.17	0.30	0.21	0.18	0.26	0.06	-0.02	0.81	0.00	0.17	0.46	0.18	0.37	0.45	-0.05	0.33	0.22	0.26
PC2	0.15	0.11	0.31	0.18	0.17	0.20	0.10	-0.03	0.88	0.04	0.24	0.47	0.15	0.37	0.31	0.09	0.23	0.17	0.21
PC3	0.24	0.14	0.39	0.23	0.20	0.22	0.09	-0.05	0.84	-0.01	0.22	0.48	0.11	0.37	0.35	0.00	0.30	0.24	0.27
PE1	0.32	0.23	0.35	0.28	0.30	0.20	0.02	0.27	0.26	0.81	0.21	-0.04	0.11	-0.05	0.31	-0.04	0.30	0.22	0.26
PE2	0.29	0.25	0.30	0.23	0.26	0.24	0.06	0.00	0.35	0.85	0.17	-0.03	0.07	-0.02	0.28	0.07	0.28	0.21	0.33
PE3	0.27	0.26	0.27	0.26	0.30	0.21	0.09	-0.04	0.30	0.85	0.15	-0.07	0.08	-0.03	0.25	0.04	0.22	0.17	0.26
PE4	0.40	0.39	0.00	0.35	0.32	0.10	0.26	-0.01	0.19	0.76	0.18	0.39	0.30	0.41	0.24	0.09	0.22	0.15	0.24
PFC2	0.35	0.36	-0.04	0.30	0.27	0.15	0.24	0.30	0.39	0.34	0.89	0.34	0.30	0.39	0.29	0.11	0.23	0.18	0.24
PFC3	0.34	0.53	-0.01	0.19	0.23	0.17	0.24	0.36	0.36	0.35	0.76	0.20	0.09	0.27	0.81	-0.10	0.39	0.20	0.20
PFC4	0.33	0.45	-0.05	0.22	0.26	0.17	0.35	0.17	0.30	0.19	0.74	0.20	0.26	0.32	0.47	0.30	0.25	0.23	0.26
PI1	0.25	0.04	0.31	0.29	0.79	0.18	0.37	0.11	0.31	0.15	0.11	0.85	0.24	0.27	0.46	0.30	0.24	0.35	0.20
PI3	-0.01	-0.05	0.09	0.00	-0.04	0.07	0.04	0.09	-0.01	0.37	0.17	0.82	0.24	0.27	0.47	0.34	0.30	0.32	0.22
PI4	0.26	0.20	0.22	0.21	0.23	0.35	0.32	0.28	-0.11	0.38	0.11	0.84	0.35	0.47	0.48	0.34	0.31	0.28	0.21
PSE1	0.17	0.21	0.11	0.10	0.15	0.17	0.17	0.18	0.15	0.11	0.11	0.07	0.79	0.43	-0.01	0.37	0.19	0.29	0.87
PSE2	0.41	0.41	0.30	0.26	0.24	0.24	0.35	0.37	0.37	0.37	-0.05	-0.02	0.84	0.48	-0.11	0.38	0.18	0.35	0.87
PSE3	0.26	0.20	0.22	0.21	0.87	0.87	0.82	0.10	0.19	0.18	0.17	0.24	0.83	0.19	0.11	0.38	0.17	0.29	0.82
R1	0.30	0.23	0.26	0.24	0.06	0.35	0.36	-0.04	0.30	0.27	0.15	0.25	0.25	0.80	0.27	0.15	0.24	0.27	0.10
R2	0.27	0.26	0.30	0.21	0.09	0.34	0.53	-0.01	0.19	0.23	0.17	0.28	0.26	0.86	0.18	0.06	0.27	0.00	-0.04
R3	0.00	0.35	0.32	0.10	0.26	0.33	0.45	-0.05	0.22	0.26	0.17	0.23	0.39	0.74	0.20	0.10	0.26	0.35	0.30
SE1	-0.04	0.30	0.27	0.15	0.24	0.25	0.04	0.31	0.29	0.79	0.18	0.79	0.28	0.07	1.00	0.09	0.30	0.32	0.27
SI1	0.11	-0.05	-0.04	-0.03	0.14	-0.02	0.23	0.35	0.32	0.28	0.30	0.20	0.47	0.17	0.35	0.87	0.30	0.29	0.23
SI2	0.07	-0.02	-0.03	0.04	0.07	-0.03	0.25	0.30	0.29	0.23	0.26	0.24	0.46	0.18	0.37	0.88	0.27	0.27	0.26
SI3	0.08	-0.03	-0.07	0.06	0.00	-0.05	0.26	0.27	0.27	0.26	0.30	0.21	0.47	0.15	0.37	0.82	0.20	0.18	0.14
SP1	0.30	0.41	0.39	0.31	0.25	0.44	0.19	0.39	0.39	0.36	0.53	0.45	0.43	0.48	0.31	0.35	0.75	-0.02	0.26
SP2	0.30	0.39	0.34	0.26	0.28	0.29	0.11	-0.08	0.00	-0.04	-0.01	-0.05	-0.01	-0.11	0.09	0.00	0.73	-0.03	0.20
SP3	0.36	0.36	0.35	0.27	0.23	0.34	0.23	0.35	0.32	0.28	0.30	0.20	0.02	0.26	0.28	0.45	0.75	0.41	0.22
SR1	0.17	0.30	0.19	0.21	0.18	0.26	0.25	0.30	0.29	0.23	0.26	0.24	0.06	0.30	0.31	0.43	-0.01	1.00	0.21
T1	0.11	0.31	0.15	0.18	0.17	0.20	0.26	0.27	0.27	0.26	0.30	0.21	0.09	0.27	0.22	0.26	0.19	0.23	0.92
T2	0.14	0.39	0.24	0.23	0.20	0.22	0.20	0.20	0.18	0.14	0.15	0.18	0.17	0.10	0.17	0.21	0.23	0.26	0.74

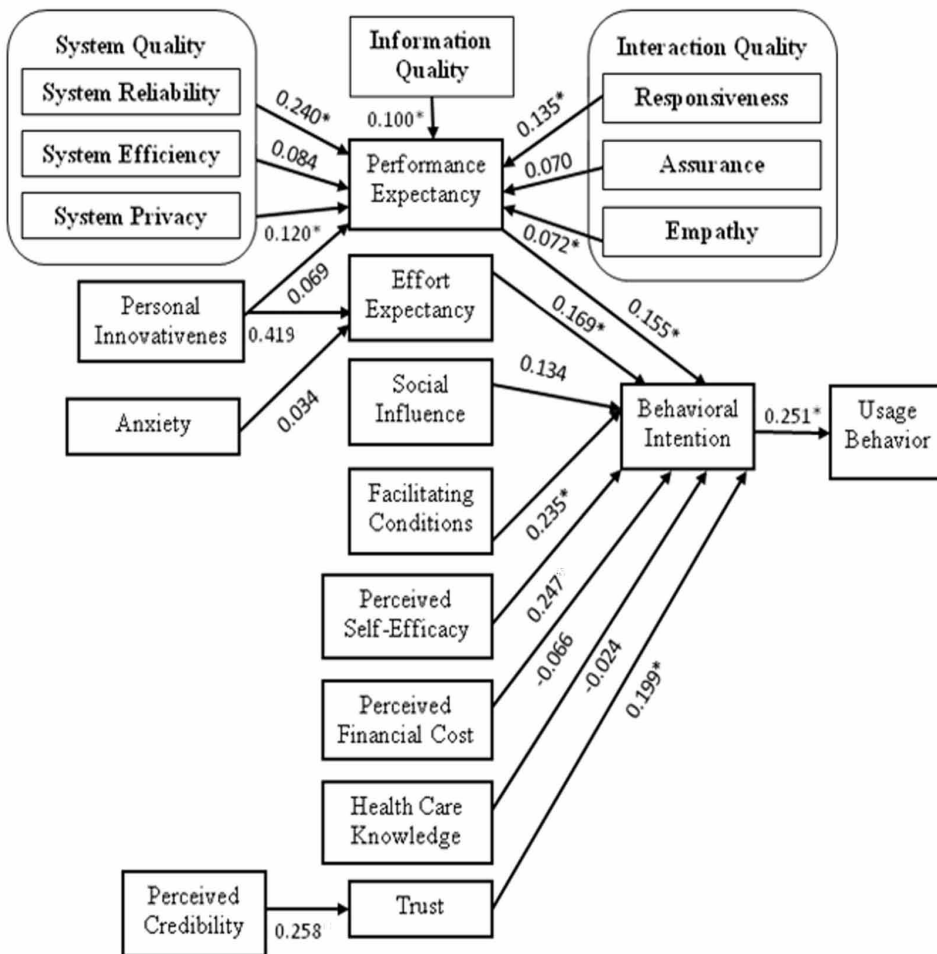
Table 6. Path Coefficients, t-statistics and Hypotheses Results

	Path Coefficients	Standard Deviation	Standard Error	T Statistics	Results
A -> EE	0.034	0.032046	0.032046	1.074575	Not Supported
As -> PE	0.070	0.059241	0.059241	1.188886	Not Supported
BI -> UB	0.251	0.028826	0.028826	8.718895	Supported
E -> PE	0.072	0.035365	0.035365	2.039735	Supported
EE -> BI	0.169	0.039409	0.039409	4.276606	Supported
FC -> BI	0.235	0.033624	0.033624	6.993609	Supported
HCK -> BI	-0.024	0.026923	0.026923	0.885092	Not Supported
IQ -> PE	0.100	0.03468	0.03468	2.897375	Supported
PC -> T	0.258	0.033036	0.033036	1.796164	Not Supported
PE -> BI	0.155	0.039446	0.039446	3.923490	Supported
PFC -> BI	-0.066	0.036704	0.036704	1.802751	Not Supported
PI -> EE	0.419	0.032311	0.032311	1.560968	Not Supported
PI -> PE	0.069	0.056968	0.056968	1.218481	Not Supported
PSE -> BI	0.247	0.033171	0.033171	1.440385	Not Supported
R -> PE	0.135	0.031652	0.031652	4.264635	Supported
SE -> PE	0.084	0.052828	0.052828	1.588044	Not Supported
SI -> BI	0.134	0.050458	0.050458	1.663493	Not Supported
SP -> PE	0.120	0.036754	0.036754	3.267334	Supported
SR -> PE	0.240	0.053026	0.053026	4.517725	Supported
T -> BI	0.199	0.43757	0.43757	2.112540	Supported

services and the working/living styles of their target customers. That is, putting efforts in designing suitable services and infrastructures to meet specific needs of different customer segments. Both government and private sector hospitals and clinics are already showing a lot of interests and concerns in this regard. However, city hospitals need to work more towards the development of such conditions for the city dwellers. Strong and correct comprehension on available facilitating conditions is important to ensure to build the right perception in the mind of the target market by showing repeatedly that all they need is a mobile phone of any type and a mobile connection mainly to take the benefits of m-Health services.

Trust is another important construct that can influence behavioral intention of m-Health services as per the findings of this study and this is similar to Mohamed et al. (2011), El-Wajeeh et al. (2014) and Nisha et al. (2015). A crucial link to trust is the perceived credibility of such services, which is why potential users are more likely to trust the service if they are convinced with the credibility of the services and of the providers. However, in the current study this result is opposite to the findings of Koenig-Lewis et al. (2010), Dasgupta et al. (2011) and Yu (2012). Marketers can use this insight and focus on developing positive experiences among the early adopters. Once the early adopters are convinced and trust is built and spread in the market, early majority and late majority will be netted accordingly. To build trust, successful cases may be communicated in the form of testimonials to reach both the external and internal information search sources. Experts and celebrity endorsements with

Figure 2. Results of Structural Equation Modeling



assurance in different communications may also be used. NGOs, who already have built a trust, may play an important role to communicate the assurance of such services to the urban markets as well.

The study drills that most of the current and potential users of m-Health services tend to judge the importance of the service based on the required effort expectancy for it. Respondents who expect less effort input in the service consuming process, especially at the adoption stage like that of m-Health services in Bangladesh, are more likely to show positive attitude in embracing the service. This finding is consistent with the evidence provided by Moores (2012), Sun et al. (2013) and Nisha et al. (2016). By making sure that the target market perceives the efforts needed to avail these services as an ease, companies can net a positive attitude towards these services. Communications of the providers, particularly of the city hospitals, should focus more on the actual handiness of such services.

Performance expectancy is the next most important construct according to the research findings of this study. Sustainable relative advantages of m-Health service such as saving time, receiving immediate and accurate healthcare advices, etc. play an important role in shaping behavior in terms

Table 7. PLS results with moderators

	Dependent Variable	
	Behavioral Intention	Usage Behavior
R ²	0.409	0.632
R ² _{adjusted}	0.409	0.632
Performance Expectancy (PE)	0.155*	
Effort Expectancy (EE)	0.169*	
Social Influence (SI)	0.134*	
Facilitating Conditions (FC)	0.235*	
Perceived Self-Efficacy (PSE)	0.247*	
Trust (T)	0.199*	
Gender	0.050*	
PE x Age	0.048*	
EE x Age	0.059*	
SI x Age	0.017*	
FC x Age	0.060*	
EE x Gender	0.051*	
PFC x Gender	0.051*	
T x Gender	0.032*	
Behavioral Intention (BI)		0.251*

*significant at 0.05

of adopting such new technologies. Sun et al. (2013) and Nisha et al. (2016) also found such similar results in their studies. The underlying cause behind such result is the novelty of such technology in the culture of Bangladesh, where most of the errands are preferred to be served in a traditional manner from physical locations. Take away for marketers from this finding is to ensure a lot of confidence among the users by highlighting the value propositions of such service with their importance in their daily life through the marketing mix of the companies. Clinching benefits such as the quality of system and of information, high responsiveness with empathy, ease of using m-Health services and the relative conveniences (outcomes) that are attached with such usages should be used as the major selling ideas of their communication campaigns to build a strong positive comprehension in the response process of the target market. The providers must also ensure a lot of empathy and a high level of responsiveness while providing the accurate information through the call center personnel to the users. They must keep in mind that one negative case in terms of accurate and quick response with empathy may lead to decreasing brand equity and hence, hospitals and clinics should train the front liners accordingly. Developing a sustainable system which ensures privacy and efficiency to support the clinching benefits of m-Health services is additionally important to encourage the consumption of such services among the city dwellers of Bangladesh.

In terms of the moderating consequences of age and gender, this study indicates that age significantly moderates the effect of effort expectancy, facilitating conditions, performance expectancy and social influence towards behavioral intention for mobile health services. This result is an outcome of the time of the penetration of this technology in Bangladesh. People, in general, today are more experienced in using technological products/services than they were several years ago and since m-Health is a new concept for the local citizens, such findings are not surprising.

Local older people are already used to and are comfortable using traditional and physical sources for healthcare services and they are not very much exposed or used to mobile phones and internet technology compared to the new generation. This situation is just another consequence of the recent globalization and affordability of technology across the world. Similar results were also identified by Gilbert et al. (2004) and Jung (2008) in their studies. The implication here for business is that, instead of developing m-Health services from the holistic viewpoint, marketers may customize their services to allow mature customers to choose a simple m-Health version.

Moreover, gender too has an important role to play in terms of shaping behavioral intention of city dwellers towards the use of mobile health services in Bangladesh. As per this study, male respondents are found to be more price sensitive than female respondents with a higher effort expectancy rate. This finding is partially consistent to Laukkanen and Pasanen (2008) and Cruz et al. (2010) in terms of price sensitivity. However, it opposes the findings of Venkatesh and Morris (2000) with regard to effort expectancy. On the other hand, female respondents are found to be more concerned about the trust factor related to mobile health services than their male counterparts. Implications for managers will be to create a message for their communication in a way that showcases the trust factor using female experts as the source of communication so that female viewers may be able to relate themselves with the story communicated. To boost the adoption rate of m-Health services for the male city dwellers, a favorable price appeal may be used to address the price sensitivity issue and special demonstrations, trainings, articles or free trials regarding m-Health services may also help.

As such, marketers can capitalize on these evidences in order to bag more people towards m-Health services in Bangladesh.

LIMITATIONS AND FUTURE RESEARCH DIRECTIONS

This study has several limitations like other empirical past studies on technology acceptance. First, the conclusions drawn from this study are based solely on the urban population, specifically people residing in Dhaka city of Bangladesh. Future research can explore the behavioral intention of people of other major cities or even the rural areas of the country. A similar research can also be done to examine the antecedents and consequences of the acceptance and use of m-Health services for different countries around the world. Second, a longitudinal study can be adopted in future works to examine and compare the research model in different time periods, thereby providing a better insight into the adoption of m-Health services in Bangladesh. Third, other than the constructs used in this study, there can be various other factors that can influence the acceptance and use of m-Health services. Further research considering different constructs can enhance the understanding of precise determinants for m-Health services in Bangladesh. Finally, future research efforts can use alternate models to explore additional constructs that can shape the behavioral intention for the use of m-Health services.

REFERENCES

- Agarwal, R., & Prasad, J. (1998). A conceptual and operational definition of personal innovativeness in the domain of information technology. *Information Systems Research*, 9(2), 204–215. doi:10.1287/isre.9.2.204
- Agarwal, S., Perry, H. B., Long, L. A., & Labrique, A. B. (2015). Evidence on feasibility and effective use of mHealth strategies by frontline health workers in developing countries: Systematic review. *Tropical Medicine & International Health*, 20(8), 1003–1014. doi:10.1111/tmi.12525 PMID:25881735
- Akter, S., D'Ambra, J., & Ray, P. (2010). User perceived service quality of m-Health services in developing countries. In *18th European Conference on Information Systems: conference proceedings*, University of Pretoria. Retrieved August 4, 2014 from <http://ro.uow.edu.au/cgi/viewcontent.cgi?article=4188&context=commpapers>>
- Akter, S., Ray, P., & D'Ambra, J. (2013). Continuance of mHealth services at the bottom of the pyramid: The roles of service quality and trust. *Electronic Markets*, 23(1), 29–47. doi:10.1007/s12525-012-0091-5
- Ami-Narh, J. T., & Williams, P. A. H. (2012). A revised UTAUT model to investigate e-Health acceptance of health professionals in Africa. *Journal of Emerging Trends in Computing and Information Sciences*, 3(10), 1383–1391.
- Angst, M. C., & Agarwal, R. (2009). Adoption of electronic health records in the presence of privacy concerns: The Elaborate Likelihood Model and individual persuasion. *Management Information Systems Quarterly*, 33(2), 339–370. doi:10.2307/20650295
- Boontarig, W., Chutimaskul, W., Chongsuphajsiddhi, W., & Papasratorn, B. (2012). Factors influencing the Thai elderly intention to use smartphone for e-Health services. In *IEEE Symposium on Humanities, Science and Engineering Research* (pp. 242-246). doi:10.1109/SHUSER.2012.6268881
- Boudreaux, E. D., Waring, M. E., Hayes, R. B., Sadasivam, R. S., Mullen, S., & Pagoto, S. (2014). Evaluating and selecting mobile health apps: Strategies for healthcare providers and healthcare organizations. *Translational Behavioral Medicine*, 4(4), 363–371. doi:10.1007/s13142-014-0293-9 PMID:25584085
- Brian, R. M., & Ben-Zeev, D. (2014). Mobile health (mHealth) for mental health in Asia: Objectives, strategies, and limitations. *Asian Journal of Psychiatry*, 10(1), 96–100. doi:10.1016/j.ajp.2014.04.006 PMID:25042960
- Burner, E., Menchine, M., Taylor, E., & Arora, S. (2013). Gender differences in diabetes self-management: A mixed-methods analysis of a mobile health intervention for inner-city Latino patients. *Journal of Diabetes Science and Technology*, 7(1), 111–118. doi:10.1177/193229681300700113 PMID:23439166
- Cairney, J., Veldhuizen, S., Vigod, S., Streiner, D. L., Wade, T. J., & Kurdyak, P. (2014). Exploring the social determinants of mental health service use using intersectionality theory and CART analysis. *Journal of Epidemiology and Community Health*, 68(2), 145–150. doi:10.1136/jech-2013-203120 PMID:24098046
- Campbell, D. T., & Fiske, D. W. (1959). Convergent and discriminant validation by the multitrait- multimethod matrix. *Psychological Bulletin*, 56(2), 81–105. doi:10.1037/h0046016 PMID:13634291
- Chin, W. W. (1998). The partial least squares approach to structural equation modeling. *Modern Methods for Business Research*, 295(2), 295–336.
- Chin, W. W., Marcolin, B. L., & Newsted, P. R. (2003). A partial least squares latent variable modeling approach for measuring interaction effects: Results from a Monte Carlo Simulation study and an Electronic-Mail Emotion/Adoption study. *Information Systems Research*, 14(2), 189–217. doi:10.1287/isre.14.2.189.16018
- Compeau, D. R., & Higgins, C. A. (1995). Computer self-efficacy: Development of a measure and initial test. *Management Information Systems Quarterly*, 19(2), 189–211. doi:10.2307/249688
- Crotts, J. (1999). Consumer decision making and prepurchase information search. In *Consumer Behavior in Travel and Tourism* (pp. 149–168). Binghamton, NY: The Haworth Hospitality Press.
- Cruz, P., Neto, L. B. F., Munoz-Gallego, P., & Laukkanen, T. (2010). Mobile banking rollout in emerging markets: Evidence from Brazil. *International Journal of Bank Marketing*, 28(5), 342–371. doi:10.1108/02652321011064881
- Dasgupta, S., Paul, R., & Fuloria, S. (2011). Factors affecting behavioral intentions towards mobile banking usage: Empirical evidence from India. *Romanian Journal of Marketing*, 3(1), 6–28.

- Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. *Management Information Systems Quarterly*, 13(3), 319–340. doi:10.2307/249008
- Davis, F. D., Bagozzi, R. P., & Warshaw, P. R. (1989). User acceptance of computer technology: A comparison of two theoretical models. *Management Science*, 35(8), 982–1003. doi:10.1287/mnsc.35.8.982
- Deglise, C., Suggs, L. S., & Odermatt, P. (2012). SMS for disease control in developing countries: A systematic review of mobile health applications. *Journal of Telemedicine and Telecare*, 18(5), 273–281. doi:10.1258/jtt.2012.110810 PMID:22826375
- DeLone, W. H., & McLean, E. R. (2003). Information systems success: The quest for the dependent variable. *Information Systems Research*, 3(1), 60–95. doi:10.1287/isre.3.1.60
- Deng, Z., Mo, X., & Liu, S. (2014). Comparison of the middle-aged and older users' adoption of mobile health services in China. *International Journal of Medical Informatics*, 83(3), 210–224. doi:10.1016/j.ijmedinf.2013.12.002 PMID:24388129
- Directorate General of Health Services (DGHS). (2014). *Health information system & e-Health*. Retrieved 23 August 2014 from <http://www.dghs.gov.bd/index.php/en/ehealth/our-ehealth-eservices/84-english-root/ehealth-eservice/97-telimedicine-services-in-community-clinics>
- Domínguez-Mayo, F. J., Escalona, M. J., Mejías, M., Aragón, G., García-García, J. A., Torres, J., & Enríquez, J. G. (2015). A strategic study about quality characteristics in e-Health systems based on a systematic literature review. *The Scientific World Journal*.
- El-Wajeeh, M., Galal-Edeen, G., & Mokhtar, H. (2014). Technology acceptance model for mobile health systems. *IOSR Journal of Mobile Computing and Acceptance*, 1(1), 21–33.
- Evans, W. D., Abrams, L. C., Poropatich, R., Nielsen, P. E., & Wallace, J. L. (2012). Mobile health evaluation methods: The Text4baby case study. *Journal of Health Communication*, 17(1), 22–29. doi:10.1080/10810730.2011.649157 PMID:22548595
- Fornell, C., & Larcker, D. F. (1981). Evaluating structural equation models with unobservable variables and measurement error. *JMR, Journal of Marketing Research*, 18(1), 39–50. doi:10.2307/3151312
- Fox, S. (2011). *The social life of health information 2011*. Washington, DC: Pew Internet & American Life Project.
- Free, C., Phillips, G., Watson, L., Galli, L., Felix, L., Edwards, P., & Haines, A. (2013). The effectiveness of mobile-health technologies to improve health care service delivery processes: A systematic review and meta-analysis. *PLoS Medicine*, 10(1), e1001363. doi:10.1371/journal.pmed.1001363 PMID:23458994
- Gagnon, M. P., Ngangue, P., Payne-Gagnon, J., & Desmartis, M. (2015). m-Health adoption by healthcare professionals: A systematic review. *Journal of the American Medical Informatics Association*. doi:10.1093/jamia/ocv052 PMID:26078410
- Gilbert, D., Balestrini, P., & Littleboy, D. (2004). Barriers and benefits in the adoption of e-government. *International Journal of Public Sector Management*, 17(4), 286–301. doi:10.1108/09513550410539794
- Hasanain, R. A., Vallmuur, K., & Clark, M. (2015). Electronic medical record systems in Saudi Arabia: Knowledge and preferences of healthcare professionals. *Journal of Health Informatics in Developing Countries*, 9(1). Retrieved 15 December 2016 from <http://jhidc.org/index.php/jhidc/article/view/135>
- Henseler, J., Ringle, C. M., & Sinkovics, R. R. (2009). The use of partial least squares path modeling in international marketing. *Advances in International Marketing*, 20(1), 277–319.
- Hoque, M. R., Karim, M. R., & Amin, M. B. (2015). Factors affecting the adoption of mHealth services among young citizen: A Structural Equation Modeling (SEM) approach. *Asian Business Review*, 5(2), 60–65. doi:10.18034/abr.v5i2.416
- Huang, E. Y., Lin, S. W., & Fan, Y. C. (2015). MS-QUAL: Mobile service quality measurement. *Electronic Commerce Research and Applications*, 14(2), 126–142. doi:10.1016/j.elerap.2015.01.003
- Hung, S., Ku, C., & Chang, C. (2003). Critical factors of WAP services adoption: An empirical study. *Electronic Commerce Research and Applications*, 2(1), 42–60. doi:10.1016/S1567-4223(03)00008-5

- Jackson, J. D., Mun, Y. Y., & Park, J. S. (2013). An empirical test of three mediation models for the relationship between personal innovativeness and user acceptance of technology. *Information & Management*, 50(4), 154–161. doi:10.1016/j.im.2013.02.006
- James, D. C., Harville, C. I. I., Whitehead, N., Stelfox, M., Dodani, S., & Sears, C. (2015). Willingness of African American women to participate in e-Health/m-Health research. *Telemedicine Journal and e-Health*. doi:10.1089/tmj.2015.0071 PMID:26313323
- Jung, M. (2008). From health to e-Health: Understanding citizens' acceptance of online health care [doctoral thesis]. Luleå University of Technology, Sweden. Retrieved 08 August 2014 from <http://epubl.ltu.se/1402-1544/2008/68/LTU-DT-0868-SE.pdf>
- Kahn, J. G., Yang, J. S., & Kahn, J. S. (2010). Mobile health needs and opportunities in developing countries. *Health Affairs*, 29(2), 252–258. doi:10.1377/hlthaff.2009.0965 PMID:20348069
- Khatwani, G., & Srivastava, P. R. (2015a). Employing group decision support system for the selection of internet information search channels for consumers. *International Journal of Strategic Decision Sciences*, 6(4), 72–93. doi:10.4018/IJSDS.2015100105
- Khatwani, G., & Srivastava, P. R. (2015b). Identifying organization preferences of internet marketing channels using Hybrid Fuzzy MCDM theories. *Journal of Electronic Commerce in Organizations*, 13(4), 26–54. doi:10.4018/JECO.2015100102
- Koenig-Lewis, N., Palmer, A., & Moll, A. (2010). Predicting young consumers' take up of mobile banking services. *International Journal of Bank Marketing*, 28(5), 410–432. doi:10.1108/02652321011064917
- Kohnke, A., Cole, M. L., & Bush, R. (2014). Incorporating UTAUT predictors for understanding home care patients' and clinician's acceptance of healthcare telemedicine equipment. *Journal of Technology Management & Innovation*, 9(2), 29–42. doi:10.4067/S0718-27242014000200003
- Korp, P. (2006). Health on the Internet: Implications for health promotion. *Health Education Research*, 21(1), 78–86. doi:10.1093/her/cyh043 PMID:15994845
- Kumar, S., Nilsen, W., Pavel, M., & Srivastava, M. (2013). Mobile health: Revolutionizing healthcare through trans-disciplinary research. *Computer*, 1(1), 28–35. doi:10.1109/MC.2012.392
- Lallmahamood, M. (2007). An examination of individual's perceived security and privacy of the Internet in Malaysia and the influence of this on their intention to use e-Commerce: Using an extension of the Technology Acceptance Model. *Journal of Internet Banking and Commerce*, 12(3), 1–26.
- Lau, M. M., Cheung, R., Lam, A. Y. C., & Chu, Y. T. (2013). Measuring service quality in the banking industry: A Hong Kong based study. *Contemporary Management Research*, 9(3), 263–282. doi:10.7903/cmr.11060
- Laukkanen, T., & Pasanen, M. (2008). Mobile banking innovators and early adopters: How they differ from other online users? *Journal of Financial Services Marketing*, 13(2), 86–94. doi:10.1057/palgrave.fsm.4760077
- Lee, J., & Rho, M. J. (2013). Perception of influencing factors on acceptance of mobile health monitoring service: A comparison between users and non-users. *Healthcare Informatics Research*, 19(6), 167–176. doi:10.4258/hir.2013.19.3.167 PMID:24175115
- Lee, K. C., & Chung, N. (2009). Understanding factors affecting trust in and satisfaction with mobile banking in Korea: A modified DeLone and McLean's model perspective. *Interacting with Computers*, 21(5), 385–392. doi:10.1016/j.intcom.2009.06.004
- Lin, H. (2011). An empirical investigation of mobile banking adoption: The effect of innovation attributes and knowledge-based trust. *International Journal of Information Management*, 31(3), 252–260. doi:10.1016/j.ijinfomgt.2010.07.006
- Maddison, R., Pfaeffli, L., Stewart, R., Kerr, A., Jiang, Y., Rawstorn, J., & Whittaker, R. et al. (2014). The HEART mobile phone trial: The partial mediating effects of self-efficacy on physical activity among cardiac patients. *Frontiers in Public Health*, 2(56), 118–121. PMID:24904918
- Masrek, M. N., Uzir, N. A. and Khairuddin, I. I. (2012). Trust in mobile banking adoption in Malaysia: A conceptual framework. *Journal of Mobile Technologies, Knowledge & Society*.

- Mohamed, A. H. H. M., Tawfik, H., Al-Jumeily, D., & Norton, L. (2011). MoHTAM: A technology acceptance model for mobile health applications. In *IEEE International Conference on Developments in E-systems Engineering (DeSE)* (pp. 13-18). doi:10.1109/DeSE.2011.79
- Moore, T. T. (2012). Towards an integrated model of IT acceptance in healthcare. *Decision Support Systems*, 53(3), 507–516. doi:10.1016/j.dss.2012.04.014
- Nelson, R. R., Todd, P. A., & Wixom, B. H. (2005). Antecedents of information and system quality: An empirical examination within the context of data warehousing. *Journal of Management Information Systems*, 21(4), 199–235. doi:10.1080/07421222.2005.11045823
- Nisha, N., Iqbal, M., Rifat, A., & Idrish, S. (2015). Mobile health services: A new paradigm for health care systems. *International Journal of Asian Business and Information Management*, 6(1), 1–18. doi:10.4018/IJABIM.2015010101
- Nisha, N., Iqbal, M., Rifat, A., & Idrish, S. (2016). Exploring the role of service quality and knowledge for mobile health services. *International Journal of E-Business Research*, 12(2), 45–64. doi:10.4018/IJEER.2016040104
- Nunnally, J. C., & Bernstein, I. H. (1994). *Psychometric Theory*. New York: McGraw-Hill.
- Parasuraman, A., Zeithaml, V. A., & Malhotra, A. (2005). E-S-QUAL: A multiple-item scale for assessing electronic service quality. *Journal of Service Research*, 7(3), 213–233. doi:10.1177/1094670504271156
- Pichitchaisopa, N., & Naenna, T. (2013). Factors affecting the adoption of healthcare information technology. *EXCLI Journal*, 12(1), 413–436. PMID:26417235
- Putzer, G. J., & Park, Y. (2012). Are physicians likely to adopt emerging mobile technologies? Attitudes and innovation factors affecting smartphone use in the Southeastern United States. *Perspectives in health information management/AHIMA*, 1(1), e9.
- Rai, A., Chen, L., Pye, J., & Baird, A. (2013). Understanding determinants of consumer mobile health usage intentions, assimilation and channel preferences. *Journal of Medical Internet Research*, 15(8), e149. doi:10.2196/jmir.2635 PMID:23912839
- Rashidee, A. H. (2013, June 30). Emerging mobile health in Bangladesh. *The Daily Star*. Retrieved 12 July 2014 from <http://archive.thedailystar.net/beta2/news/emerging-mobile-Health-in-bangladesh/>
- Rogers, E. M. (1995). *Diffusion of Innovations* (4th ed.). New York: Free Press.
- Rogers, E. M. (2005). *Diffusion of Innovations* (5th ed.). New York: Free Press.
- Rousseau, D. M., Sitkin, S. B., Burt, R. S., & Camerer, C. (1998). Not so different after all: A cross-discipline view of trust. *Academy of Management Review*, 23(3), 393–404. doi:10.5465/AMR.1998.926617
- Sayyahgilani, M., Mayeh, M., & Ramayah, T. (2014). Key factors influencing the adoption of telemedicine in Malaysian public hospitals: a cross-sectional survey. In *The 2nd International Conference on e-Health and Telemedicine: conference proceedings ICEHTM '14*. Retrieved 18 August 2014 from <http://icehtm.net/2014/articles/18%20-1238.pdf>
- Sieverdes, J. C., Treiber, F., Jenkins, C., & Hermayer, K. (2013). Improving diabetes management with mobile health technology. *The American Journal of the Medical Sciences*, 345(4), 289–295. doi:10.1097/MAJ.0b013e3182896cee PMID:23531961
- Silva, B. M., Rodrigues, J. J., de la Torre Díez, I., López-Coronado, M., & Saleem, K. (2015). Mobile-health: A review of current state in 2015. *Journal of Biomedical Informatics*, 56(2), 265–272. doi:10.1016/j.jbi.2015.06.003 PMID:26071682
- Stofega, W., & Llamas, R. T. (2009). *Worldwide Mobile Phone 2009-2013 Forecast Update, IDC Document Number 217209*. Framingham, MA: IDC.
- Sun, Y., Wang, N., Guo, X., & Peng, Z. (2013). Understanding the acceptance of mobile health services: A comparison and integration of alternative models. *Journal of Electronic Commerce Research*, 14(2), 183–200.

- Sunyaev, A., Dehling, T., Taylor, P. L., & Mandl, K. D. (2014). Availability and quality of mobile health app privacy policies. *Journal of the American Medical Informatics Association*. doi:10.1136/amiajnl-2013-002605 PMID:25147247
- Tamrat, T., & Kachnowski, S. (2012). Special delivery: An analysis of mHealth in maternal and newborn health programs and their outcomes around the world. *Maternal and Child Health Journal*, 16(5), 1092–1101. doi:10.1007/s10995-011-0836-3 PMID:21688111
- Townsend, A., Leese, J., Adam, P., McDonald, M., Li, L. C., Kerr, S., & Backman, C. L. (2015). eHealth, participatory medicine, and ethical care: A focus group study of patients' and health care providers' use of health-related internet information. *Journal of Medical Internet Research*, 17(6), e155. doi:10.2196/jmir.3792 PMID:26099267
- Varshney, U. (2005). Pervasive healthcare: Applications, challenges and wireless solutions. *Communications of the Association for Information Systems*, 16(3), 57–72.
- Vedder, A., Cuijpers, C., Vantsiouri, P., & Ferrari, M. Z. (2014). The law as a 'catalyst and facilitator' for trust in e-health: Challenges and opportunities. *Law, Innovation and Technology*, 6(2), 305–325. doi:10.5235/17579961.6.2.305
- Venkatesh, V., & Davis, F. D. (2000). A theoretical extension of the technology acceptance model: Four longitudinal field studies. *Management Science*, 46(2), 186–204. doi:10.1287/mnsc.46.2.186.11926
- Venkatesh, V., & Morris, M. G. (2000). Why don't men ever stop to ask for directions? Gender, social influence and their role in technology acceptance and usage behavior. *Management Information Systems Quarterly*, 24(1), 115–139. doi:10.2307/3250981
- Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User acceptance of information technology: Toward a unified view. *Management Information Systems Quarterly*, 27(3), 425–478. doi:10.2307/30036540
- Venkatesh, V., Thong, J. Y. L., & Xin, X. (2012). Consumer acceptance and use of information technology: Extending the Unified Theory of Acceptance and Use of Technology. *Management Information Systems Quarterly*, 36(1), 157–178.
- Venkatesh, V., & Zhang, X. (2010). Unified theory of acceptance and use of technology: U.S. vs. China. *Journal of Global Information Technology Management*, 13(1), 5–27. doi:10.1080/1097198X.2010.10856507
- Wand, Y., & Wang, R. Y. (1996). Anchoring data quality in ontological dimensions. *Communications of the ACM*, 39(11), 86–96. doi:10.1145/240455.240479
- Washington, G., Ward, J., & Kameka, M. (2015). Spare me: Towards an empathetic tool for helping adolescents & teenagers cope with sickle cell. In *IEEE Proceedings of the 2015 International Conference on Healthcare Informatics (ICHI)* (pp. 555-561). doi:10.1109/ICHI.2015.104
- Watzdorf, S. V., Ippisch, T., Skorna, A., & Thiesse, F. (2010). The Influence of Provider Trust on the Acceptance of Mobile Applications: An Empirical Analysis of Two Mobile Emergency Applications. In *Ninth International Conference on Mobile Business 2010: conference proceedings* (pp. 329-336).
- West, D. (2012). How mobile devices are transforming healthcare. *Issues in Technology Innovation*, 18(1).
- Wilson, E. V., & Lankton, N. K. (2004). Modeling patients' acceptance of provider-delivered E-health. *Journal of the American Medical Informatics Association*, 11(4), 241–248. doi:10.1197/jamia.M1475 PMID:15064290
- Wu, I., Li, J., & Fu, C. (2011). The adoption of mobile healthcare by hospital's professionals: An integrative perspective. *Decision Support Systems*, 51(3), 587–596. doi:10.1016/j.dss.2011.03.003
- Wu, J., Wang, S., & Lin, L. (2007). Mobile computing acceptance factors in the healthcare industry: A structural equation model. *International Journal of Medical Informatics*, 76(1), 66–77. doi:10.1016/j.ijmedinf.2006.06.006 PMID:16901749
- Yang, A. S. (2009). Exploring adoption difficulties in mobile banking services. *Canadian Journal of Administrative Sciences*, 26(2), 136–149. doi:10.1002/cjas.102
- Yang, K. C. C. (2005). Exploring factors affecting the adoption of mobile commerce in Singapore. *Telematics and Informatics*, 22(3), 257–277. doi:10.1016/j.tele.2004.11.003

Yin, S. Y., Huang, K. K., Shieh, J. I., Liu, Y. H., & Wu, H. H. (2016). Telehealth services evaluation: A combination of SERVQUAL model and importance-performance analysis. *Quality & Quantity*, 50(2), 751–766. doi:10.1007/s11135-015-0174-4

Yu, C. (2012). Factors affecting individuals to adopt mobile banking: Empirical evidence from the UTAUT model. *Journal of Electronic Commerce Research*, 13(2), 104–121.

Nabila Nisha is currently pursuing her PhD at the Australian National University, Australia in Marketing Management. She is also employed as a Senior Lecturer at the Department of Accounting & Finance under School of Business and Economics of North South University. She completed her Bachelor's degree with dual concentration in Accounting & Finance and Marketing from North South University, Bangladesh. She received her Master's degree in Banking & Finance from University of Essex, UK. Besides teaching, she has been part of a research project on Green Banking financed by World Bank and Ministry of Education of Bangladesh. Her research interests broadly ranges across technology adoption, service sectors, and consumer resources and specifically centers upon brand extension evaluations in sharing economy. She has a number of international journal publications in USA, UK, Malaysia and India. She also has local and international book chapters and business case studies as part of her research work. She has authored two books as well, which has been published by Lambert Academic Publishing and is available in the international market.

Mehree Iqbal is a Senior Lecturer in the School of Business and Economics at North South University. Ms. Iqbal completed her Bachelor of Business Administration (BBA) Degree from North South University, Bangladesh and Masters of Science Degree in International Business and Entrepreneurship from University of Glasgow, UK. Currently, she is on study leave to pursue PhD on Social Entrepreneurship from Curtin University. She has been awarded Research Training Program (RTP) Stipend Scholarship from Australian Government. She taught courses on International Business and Entrepreneurship. In addition to teaching, Ms. Iqbal has research interest in behaviour/intention, Technology, and Social Entrepreneurship. She has published in international journals and book chapters

Afrin Rifat is a Senior Lecturer of Accounting and Finance department at the School of Business & Economics of North South University. Currently she is teaching major courses of Intermediate Accounting and Managerial Accounting at the undergraduate level. Ms. Rifat earned her Bachelor of Business Administration degree with major in finance & accounting from North South University, Bangladesh and Masters Degree in Banking and Finance from University of Essex, UK in 2010 and 2011 respectively. Her current research interests include technology acceptance models, financial statement analysis and decision-making, banking strategies and empirical research methods in finance and country specific studies.