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Abstract

Due to the low adoption rate of mHealth apps, the apps designers need to understand the factors behind adoption. But understanding the determinants of mHealth apps adoption remains unclear. Comparatively less attention has been given to the factors affecting the adoption of mHealth apps among the young generation. This study aims to examine the factors influencing behavioral intention and actual usage behavior of mHealth apps among technology prone young generation. The research model has extracted variables from the widely accepted Unified Theory of Acceptance and Use of Technology (UTAUT2) alongside privacy, lifestyles, self-efficacy and trust. Required data were collected from mHealth apps users in Bangladesh. Firstly, this study confirmed that performance expectancy, social influence, hedonic motivation and privacy exerted a positive influence on behavioral intention whereas facilitating conditions, self-efficacy, trust and lifestyle had an influence on both behavioral intention and actual usage behavior. Secondly, the Neural Network Model was employed to rank relatively significant predictors obtained from structural equation modeling (SEM). This study contributes to the growing literature on the use of mHealth apps in trying to elevate the quality of patients' lives. The new methodology and findings from this study will significantly contribute to the extant literature of technology adoption and mHealth apps adoption intention especially. Therefore, for practitioners concerned with fostering mHealth apps adoption, the findings stress the importance of adopting an integrated approach centered on key findings of this study.

Keywords: mHealth apps; adoption; UTAUT2; Artificial Neural Network.

1. Introduction

Over the last few decades, Smartphones have been turned into an indispensable part of modern lifestyles. The usage of Smartphone applications, commonly known as apps, has been increased noticeably throughout the globe due to a higher penetration rate of Smartphones. The projected mobile phone subscribers globally with an unprecedented proliferation in mobile apps will reach 6.95 billion by 2020 (Statista, 2020). In this connection, mobile health applications, widely known as mHealth apps, have started to launch their scope in health care industry (Byambasuren et al., 2019, Guo et al., 2016).

Almost, all developed countries and even some developing countries have mobile penetration rate close to 100%. This has been fueling the interest in mHealth solutions as a game changer for global health (PwC, 2017). According to Kay et al. (2011), higher income countries have more mHealth initiatives than lower income countries. They also further states that European countries are more active in providing mHealth services compared to African countries. In recent years, mHealth has emerged more popularity in developing countries where many governments are recognizing the possible benefits of mHealth and have integrated it into their plans to attain their health system targets aligned with Sustainable Development Goals (SDGs) (Wallis et al., 2017).

mHealth apps have been evolved as a major communication tool for promoting, delivering, and tracking healthcare services. Many electronic devices have been developed facilitating healthcare delivery systems and improving the effectiveness of healthcare services (Sadegh et al., 2018, Rajak and Shaw, 2019). However, it has been observed that there are more than 325,000 mHealth apps accessible at all major apps stores which are estimated to increase by approximately 25% each year in numerous health categories such as cardiology, diabetes, fitness, obesity, chronic diseases and smoking cessation (Shin et al., 2017). Furthermore, globally, the approximate value of the mHealth apps market is likely to achieve about US$28.320 billion in 2018 and is expected to achieve US$102.35 billion by 2023 (Liquid, 2018).

mHealth apps are growing in number dramatically and becoming increasingly available to young adults with and without chronic illness. In this era of digitalization, among different aged users, booming young generations are mostly passionate to the susceptible operational features of Smartphone devices and find the usage of technology a new custom among their peer groups in comparison to the older generations (Kim et al., 2019).

On the other hand, Bangladesh is currently in the process of adopting a framework for eHealth and mHealth, based on a decade of experiences. Bangladesh, as a densely populated country, has been preferred as the context for conducting the current study due to potential business opportunities for mHealth apps in comparison to other neighboring countries (Karim et al., 2016, Akter et al., 2013). Almost 39.73% of the total population is comprised of the young generation which is the largest market for digital offerings in upcoming years (BBS, 2018). On the other hand, the university students in Bangladesh, with the age range of 23-26 years old are at greater risk of suffering from diverse health problems (i.e. Type 2 diabetes, hypertension, heart failures, coronary and cardiovascular diseases) and on an average about 30 people across the country commit suicide every single day (Hasam and Mushahid, 2017). Young people are the future for a nation and they should be supported, nurtured and encouraged as they make their journey into adulthood and independent. There is a greater potential for mHealth services in the future among young people compared with older age groups (Rahman et al., 2017). Sustainable Development Goals (SDGs) acknowledge the young generation as one of the key target groups. To better understand its potential in

Bangladesh, it is indeed important to understand how young people use mobile phones for healthcare services (Rahman et al., 2017). With the rapid proliferation of mobile phones and the internet, in both developed and developing countries, young generation is more likely to find technology useful, be at ease about using it and find the usage of technology a norm among their peers compared with older generations (Djamasbi et al., 2010).

Healthcare in Bangladesh is a sector that has always been riddled with infrastructural difficulties, given the nation's robust population. Bangladesh lags behind in the ratio between patients, and their doctors and nurses by its neighbor (Dhaka Tribune, 2019). Moreover, the healthcare system is also troubled by the challenges of extending healthcare at affordable and accessible (Akter et al., 2010a). As for mobile technology, in Bangladesh, there are over six nationwide independently owned cell phone operators with 169.590 million subscribers at the end of March 2019 (BTRC, 2019). In Bangladesh, nearly 80% people are mobile phone subscribers, whereas 91.421 millions are internet users; 80.47 millions are mobile phone internet users and about 8.921 million are Smartphone users (BTRC, 2019). Hence, the penetration rate of Smartphone usage is fueling the vast opportunities for healthcare providers to improve the quality of healthcare delivery services with safety and efficiency via mobile apps.

Under these circumstances, the development and implementation of mHealth apps can play an alternative and imperative role to overcome these limitations in low resources settings of Bangladesh (Vatsalan et al., 2010). But the adoption of mHealth and the allied market for these services have not yet reached maturity in this country (Alam et al., 2020). mHealth has emerged in mid-1999. In 2006, the leading Cellphone operators (i.e. Grameen Phone Ltd) of Bangladesh launched digital healthcare services to their subscribers (GHWA, 2013). In May 2009, the Government also invested huge amounts of money in developing eHealth/mHealth services to ensure pregnancy related health advice. In 2012, approximately 26 mHealth initiatives, 10 telemedicine centers and 42 hospital-based centers were introduced across the country (Rahman and Hoque, 2018). In addition, Karim et al. (2016) mentioned that a total of 180 mHealth apps available in Bangladesh under seven clusters that are primarily designed to fit more or less all the major mobile devices.

Although, numerous mHealth services in Bangladesh have been developed very fast and smoothly, and many users have tried to put them into use, the adoption rate and active users remain relatively low and left over challenges for adoption (Hoque et al., 2015). Since, major portions of the population have not yet fully accepted mHealth apps as a part of their daily activities in solving their health problems, apps developers and designers should intensively promote their apps either for free download or as free trial versions before full acceptance and usage. Surprisingly, the adoption rate of mHealth apps failed to reach the expected level (Alam et al., 2020). Furthermore, a large number of mHealth/eHealth initiatives have not been successfully put into operation in the existing healthcare system. Although the young generation is technology prone customer and use diversified apps for different purposes, the rate of acceptance and usage of mHealth apps among them is significantly low (Lee and Kim, 2017). Facilitating safe mHealth services for young people should be a policy priority (Hamspire et al., 2015). However, the factors that drive mHealth adoption across young aged groups remain relatively unexplored. Thus, the following specific research questions were postulated in this study: 1) What are the key determinants of the adoption of mHealth apps among booming young generation?; and 2) What is the relative importance of the determinants of mHealth apps adoption? Therefore, indeed, it is required for mHealth apps developers to address the key influential predictors on the behavioral intention of the app's users and assimilate strategic planning to bring satisfaction and promote further usage of mHealth apps for personal healthcare management.

However, a substantial number of research about mHealth services has been found in different context of Bangladesh, i.e. mHealth apps in Bangladesh (Karim et al., 2016), readiness of the community for mHealth in rural context (Khatun et al., 2015), perceived services quality dynamics (Akter et al., 2010b), trustworthiness in mHealth services (Akter et al., 2011), telemedicine adoption in rural areas (Rahman and Hoque, 2018), mHealth and eHealth initiatives in Bangladesh (Ahmed et al., 2014), adoption of portable health clinics in rural areas (Hossain et al., 2019), assessing the mHealth success in Bangladesh (Hossain, 2016), adoption intention of mHealth from demand side perspective (Shareef et al., 2014), health information seeking behavior (Andaleeb, 2008), mHealth status and challenges in Bangladesh (Alam, 2018), mHealth adoption by the elderly users (Quaosar et al., 2018), mHealth adoption behavior among the patients (Alam et al., 2020) etc.

From the extant review of the literature, it has been observed that the majority of the researches have been focused on identifying the key dominant factors affecting the initial adoption of mHealth/eHealth/Telemedicine rather than mHealth apps adoption intention. Despite these numerous studies, it is also indeed necessary to provide a further understanding regarding the key influential factors affecting behavioral intention and actual usage behavior.

mHealth apps alters the diversity of healthcare services from crisis intervention to prevention of healthcare services, healthcare promotion and self-management. Thus, numerous mHealth activities are already under process in developing countries especially Bangladesh. Overall, the findings suggest that the usability of the mHealth apps in Bangladesh is not satisfactory in general and could be a potential barrier for wider adoption of mHealth services (Islam et al., 2020). Many private and public sector have invested millions of dollar in this domain. But, limited research has been conducted on the key factors affecting the intention and actual usage behavior of mHealth apps in Bangladesh context. Thus, it is not clear what factors forcing the adoption of mHealth apps in resources constrained developing countries including Bangladesh (Alam et al., 2018).

Hence, the main aims of this study are to explore the most significant determinants that could form the customers' behavioral intention and adoption of mHealth apps among the booming young generation. One of the main drawbacks of conventional statistical techniques used for the prediction of users' behavior is that they usually examine the only linear relationship among variables. To overcome this issue, the relative importance of significant variables will be determined using neural networks capable to model complex non-linear relationships (Leong et al., 2019, Akgül., 2018). In addition, the aim is to assist healthcare service providers in designing effective mHealth apps by considering the relatively important factors for prospective customers.

The remaining part of this paper is structured as follows. Section 2 represents a literature review followed by a theoretical framework and development of hypotheses in section 3. Then, section 4 describes the methodology for conducting the research. Section 5 and 6 explain the summary of data analysis and discussions of the findings accompanied by theoretical contributions and practical implications respectively. Finally, the conclusion, limitations and directions for future research are presented sequentially in section 7.

2. Literature Review

A substantial number of researches on mHealth/eHealth have been rising explosively in the last few years due to acknowledgement of the value of wireless technologies for healthcare delivery, explosive mobile phone penetration rate and massive funding initiatives in mHealth/eHealth infrastructure (Cameron et al., 2017, Wang et al., 2018).

However, identification of the influential factors behind the intention and actual usage behavior of the end users towards a new age technology has been undertaken as an essential objective with changing the functional features of a given technological service to make this adoption more attractive (Baabdullah et al., 2018). Adoption behavior of users of mHealth apps has been examined through multiple lenses such as intrinsic/extrinsic motivation, ease of use, usefulness, self-efficacy, control, risk beliefs, privacy concerns and autonomy (Zhao et al., 2018). A considerable number of studies regarding mHealth apps adoption in different contexts are shown in the Table 1. Most of the studies focus on investigating the factors affecting mHealth apps adoption in a different context and user groups rather than young generation. This clearly explains that mHealth apps are still a subject worthy of research and study.

However, a recent study conducted by Duarte & Pinho (2019) employed UTAUT2 model for identification of factors affecting mHealth adoption. They found that performance expectancy, hedonic motivation and habit have the ability to predict mHealth adoption. Another study conducted by Dhiman et al. (2019) applying UTAUT2 model also explored that significant predictors of Smartphone health fitness apps adoption intention include effort expectancy, social influence, perceived value, habit and personal innovativeness.

Besides, a meta-analysis administered by Zhao et al. (2018) revealed the role of perceived usefulness, perceived risk, subjective norms, perceived ease of use, trust and attitudes were significantly and positively associated with behavioral intention. Similarly, Azhar and Dhillon (2016) conducted a systematic literature review that revealed seven key factors namely; perceived usefulness, social influence, perceived privacy risk, perceived ease of use, self-efficacy, attitude and behavioral intention which were found to have a significant association with the actual adoption of mHealth apps. Though, a handful number of researches have been conducted on mHealth adoption and reported the key contributors, only a few numbers of studies have been explicitly focused on mHealth apps adoption in the context of Bangladesh (i.e. Islam et al., 2020; Rahman et al., 2018; Alam et al., 2020; Hoque et al., 2017; Karim et al., 2016).

Table 1
Summary of the researches on mHealth adoption in different developed and developing countries

Authors/Years	Theoretical Frameworks/Models	Key Findings
Okumus et al. (2018)	Extended UTAUT	Performance expectancy, social influence and effort expectancy, Innovativeness.
Cho (2016)	PAM & TAM	Perceived usefulness, perceived ease of use, confirmation, and satisfaction.
Yang (2013)	TPB, TAM & Gratification Theory	Perceived usefulness, perceived enjoyment, ease of use, subjective norms and perceived behavioral control.
Chang et al. (2016)	TAM and TPB	Perceived usefulness, perceived ease of use, social influence, attitudes, self-efficacy, involvement and perceived behavioral control.
Wu et al. (2011)	TAM and TPB	Perceived usefulness, subjective norms, perceived behavioral control and attitudes.
Gao et al. (2015)	UTAUT2, PMT & Privacy Calculus Theory	Hedonic motivation, perceived privacy risk, social influence, perceived vulnerability and functional congruence.
Phichitchaisopa and Naenna (2013)	UTAUT	Performance expectancy, facilitating conditions, effort expectancy.
Lim et al. (2011)	Extended TAM	Perceived usefulness, self-efficacy, prior experiences.
Byomire and Maiga (2015)	TAM and UTAUT	Perceived ease of use, perceived usefulness, facilitating conditions, social influence, perceived value, workflow practices and behavioral intention.
Hoque and Sorwar (2017)	Extended UTAUT	Performance expectancy, social influence, effort expectancy, technology anxiety and resistance to change.
Yuan et al. (2015)	UTAUT2	Performance expectancy, hedonic motivations, price value, and habit.
Sun et al. (2013)	Integrated Model	Performance expectancy, social influence, effort expectancy, threat appraisals and facilitating conditions.
Hoque (2016)	Extended TAM	Perceived usefulness, trust, subjective norms and perceived ease of use.
Sezgin et al. (2018)	(mHealth) M-TAM	Effort Expectancy, mobile anxiety, perceived service availability and technical training and support.
Cho et al. (2014)	Extended TAM	Subjective norm, health consciousness, health information orientation, and Internet health information use efficacy.
Balapour et al. (2019)	Traditional Adoption Approach	Perceived mobile technology identity (MTI), perceived related IT experience, and perceived self-efficacy.
Mohamed et al. (2011)	Extended TAM	Social, cultural, and technological constructs, perceived usefulness and perceived ease of use.
Kang (2014)	Extended TAM	Performance expectancy, effort expectancy, social influence, entertainment and communication.
Alam et al. (2019)	Extended UTAUT (Cross-country Analysis)	Performance expectancy, Social influence, Facilitating Conditions, Perceive Reliability for Bangladesh. Performance expectancy, effort expectancy, social influence, price value for China
Alam et al. (2020)	Extended UTAUT	Performance expectancy, Social influence, Facilitating Conditions, Perceive Reliability
Kaium et al. (2019)	Systematic Literature review	Infrastructural, functional, operational and social benefits, confidentiality, social aspect, skill and financial aspect etc.
Hoque & Sorwar (2016)	UTAUT	Performance expectancy, Social influence, Technology Anxiety and Resistance to change
Dwivedi et al. (2016)	Generalized Model	Performance expectancy, Effort expectancy, Hedonic Motivation, Price value, Social Influence, Facilitating Conditions and Waiting time.

[Note: UTAUT: Unified Theory of Acceptance and Use of Technology; TAM: Technology Acceptance Model; PAM: Post-Acceptance Model; PMT: Protection Motivation Theory; TPB: Theory of Planned Behavior].

However, this study differs from the previously mentioned studies, as it expands the range of factors that might impact the adoption of mHealth apps within the context of Bangladesh. This study tries to bridge the gap mentioned above by exploring the determinants behind the adoption of mHealth apps among the booming youth people. This is done by extending the original UTAUT2 model in the environmental setting of developing countries. Due to socio-economic differences in the market, Models/theories used in Western countries may not be equally applicable in the context of developing countries. Therefore, which antecedents affect the adoption by users is still a puzzle for policy makers in developing countries (Dwivedi et al., 2016).

Because of the existence of linear and nonlinear relationships between independent and dependent variables, this study employs neural network to predict the factors that influence consumers' mHealth adoption decisions. Besides, the neural network model outperformed the regression model in adoption prediction, and captured the non-linear relationships between predictors. The results from the neural network will then be compared to the ones obtained from multiple regression analysis to determine which one offers better predictive power.

3. Theoretical Framework and Hypothesis Development

A handful number of models has been constructed and employed to examine information system (IS) acceptance and usage intention over the last few decades (Dwivedi et al., 2017a, Dwivedi et al., 2013). A careful investigation of the theories/models revealed the importance of taking into consideration as a theoretical basis best suited to the customer's view point (Rana et al., 2016, Venkatesh et al., 2012, Dwivedi et al., 2017b). Therefore, in the quest of searching a suitable model/theory covering almost all constructs determining the young generation's adoption intention of mHealth apps, UTAUT2 model was chosen as a theoretical basis for its higher predictive power particularly applicable in the users' context. UTAUT2 model is the revised and upgraded version of the Unified Theory of Acceptance and Use of Technology (UTAUT) model developed by Venkatesh et al. (2003) with four influencing constructs of behavioral intention, namely performance expectancy, effort expectancy, social influence and facilitating conditions. Later on, hedonic motivation, price value and habit have been added to the original UTAUT model and renamed it as UTAUT2 model (Venkatesh et al., 2012). As mentioned in earlier studies, application of UTAUT2 focusing on mHealth apps is still deficient. Thus, to apply UTAUT2 in certain special IT applications, Venkatesh et al. (2012) suggested that further modifications and revisions be made.

Due to the aforementioned limitations of UTAUT2 model, in this study, it is assumed that non-technical factors (i.e. personal factors) have an influence on attitude towards the adoption of mHealth apps. Besides, most of the young adults have a modern and western lifestyle, and are socially active users and conspicuously well-educated (Gao et al., 2014). In addition, they always try to lead visible and materialistic lives. So, it is needed to integrate lifestyle into IT adoption models/theories to enhance the acceptability of the adoption theory/model. The role of self-efficacy has also been recognized over the current literature as one of the most vital factors determining the users' perception towards such novel technologies (Dwivedi et al., 2017a). Along with various intrinsic factors, trust and privacy have been recognized as other looming challenges for the successful acceptance and actual use of eHealth/mHealth (Hoque, 2016). Therefore, this empirical research expands UTAUT2 model by incorporating the four additional relevant variables; lifestyle, privacy, self-efficacy and trust due to increasing the usage of mHealth apps. Therefore, the following hypotheses were developed and discussed sequentially.

3.1 Performance Expectancy (PE)

PE is defined as the extent to which a user perceives utilizing the new Information System (IS) will assist him/her to accomplish in job performance (Venkatesh et al., 2003). Broadly speaking, customers seem to be more motivated to use and accept new technology if they perceive that this technology is more advantageous and useful in their daily life (Alalwan et al., 2017). Lu et al. (2009) explored that PE had significantly influenced users to accept mobile services. However, an application that seems to be more usefulness is more likely to be adopted than applications that can´t play a role in achieving this performance (Altmann and Gries, 2017). PE is the best representative of the end-users' expectations associated with adoption of mHealth apps in solving highly personalized healthcare problem. Considering the primary role of health apps providing health information, however, it is logical to argue that health conscious people will recognize mHealth apps as valuable tools for managing their personalized health problem. Furthermore, Hoque and Sorwar (2017) also revealed that PE is one of the most significant factors impacting users' behavioral intention to adopt mHealth among elderly people. Thus, if an end user realizes that mobile apps seem to be more usefulness than other traditional tools, then he or she would more likely to use mobile apps (Hew et al., 2015). Therefore, the following statement was hypothesized:

H1: PE positively influences the behavioral intention to use mHealth apps.

3.2 Effort Expectancy (EE)

EE is identified as the extent to which the degree of simplicity of usage associated with the information system (Venkatesh et al., 2003). Usually, users tend to consider the efforts required before using the information system (Venkatesh et al., 2012). In the earlier studies, EE has been recognized as a significant factor on the acceptance of innovative technology, where the degree of the ease of use associated with the information system significantly and positively affected the behavioral intention towards various new age technologies, i.e. eHealth and mHealth (Chong, 2013a). Besides, mHealth apps are designed with simplicity and convenient for the end-users to manage a personalized health problem. The lesser the efforts needed to operate apps, the more likely end-users will have continuous usage intention over the time (Yuan et al., 2015). Therefore, the following was hypothesized:

H2: EE positively influences the behavioral intention to use mHealth apps.

3.3 Social Influence (SI)

SI is identified as the extent to which an individual recognizes the beliefs of other important persons that he or she should employ the new information system (Venkatesh et al., 2003). Kim et al. (2014) explored that individual behavioral intention to accept mobile devices (i.e. Smartphone, Wireless devices) was significantly influenced by the surrounding environment that they are belonged to. Taylor et al. (2011) revealed that university students' adoption intention and actual usage of mobile apps is strongly affected by peer groups compared to their members of family members and relatives. Moreover, the majority of the young generations are more influenced by peer thoughts, opinions and activities (Al-Maghrabi et al., 2011). Additionally, Okumus et al. (2018) explored that SI played a vital role in deriving customers' behavioral intention to use mobile diet apps for healthcare management. Therefore, apps developers make it handier for patients to link with surrounding people to whom they believe their opinions, views and perceptions as crucial, which enhances their social influence in the healthcare domain (Yuan et al., 2015). Hence, the hypothesis pertaining to SI was postulated:

H3: SI positively influences the behavioral intention to use mHealth apps.

3.4 Hedonic Motivation (HM)

HM is identified as the degree of the fun, enjoyment or pleasure derived from utilizing innovation in technology, and it has been acknowledged as the vital role in determining technology acceptance and usage (Venkatesh et al., 2012). However, people having hedonic motivation pay more concentration on enjoyment, fun, entertainment and playfulness of IS/IT than people with utilitarian motivation. Individuals may use mobile apps for task performances and personal entertainment in the context of eHealth consumers as well (Cocosila and Archer, 2010). When customers realize that entertainment, fun, happiness, comfort, enjoyment, pleasure and satisfaction will be extracted from using new technology, they will be more likely to adopt this new age technology (Alalwan et al., 2015, Baabdullah, 2018). If an individual perceives that mobile apps usage is funny, enjoyable and pleasant, he or she would more likely to use mobile apps for healthcare services (Hew et al., 2015). Therefore, the following hypothesis was posited:

H4: HM positively influences the behavioral intention to use mHealth apps.

3.5 Price Value (PV)

PV refers to consumers' perceived value which is the difference between the total perceived benefits of the applications and the total monetary or non-monetary cost for using them (Venkatesh et al., 2012). Furthermore, it is required to evaluate the economic viability of mHealth apps adoption to ensure that these health promotion tools are a cost-effective channel for different end-users in different environmental settings (Dwivedi et al., 2017a). Customers will expect higher quality or better value of the services for the money paid. The role of price value has been demonstrated in diverse technology adoption; i.e. Mobile Banking, Mobile commerce and food ordering apps (Alalwan et al., 2017; Shaw and Sergueeva, 2019; Alalwan, 2020). According to Dwivedi et al. (2016), PV is one of the strong determinants of the consumers' actual purchase decision for mHealth apps. Therefore, the following hypothesis relevant to the PV is posited as follows:

H5: PV positively influences the behavioral intention to use mHealth apps.

3.6 Habit (HT)

HT is described as the point to which people intend to perform their behaviors automatically because of learning or experiences, and it has also been viewed as a perceptual variable that is the reflection of past experiences (Venkatesh et al., 2012). Once a consumer is regularized in using health apps, it will drive to continuous usage intention automatically. Besides, it is also reasonable to say that when consumers engage in health behavior, initial usage intentions will be re-activated, which positively lead to use repeatedly (Demiris et al., 2013). Habitualization of Smartphone usage has been reached at a very high level in developed countries, i.e. USA (Yuan et al., 2015). Amoroso and Lim (2017) explored that satisfied customers are more likely to habituate behavior, and hence they will show more willingness to keep using these apps continuously. Another empirical research conducted by Chuang (2011) explored that HT is one of the most vital influential determinants of intention to switch mobile services. Hence, the following hypothesis was postulated:

H6: HT positively influences the behavioral intention to use mHealth apps.

3.7 Privacy (PR)

According to Chaffey (2009), PR is defined as the extent to which the exclusive right of an individual to direct the information held about them by the third parties. Privacy of patients' data is of high importance while using mobile apps for health related information (Luxton et al., 2011). The privacy calculus model, which suggests that consumers engage in a risk–benefit analysis when they share information with the vendor, has been adopted by Xu et al. (2011). Users are concerned about the inappropriate collection, storage, profiling and use of their personal information for unintended purposes without their consent (Keith et al., 2013). However, customers are likely to disclose personal information via mobile devices if their perceived benefits of doing so are high (Wang et al., 2016). It is also revealed that PR plays critical roles in the implementation and adaptation of the mHealth systems successfully. The most important driver of privacy is the desire for information control (Anic et al., 2019). Consequently, perceived security and privacy value are to reflect new concerning issues in the perspectives of mHealth services. Therefore, the following statement was posited:

H7: PR positively influences the behavioral intention to use mHealth apps.

3.8 Facilitating Conditions (FC)

FC refers to the context in which an individual perceives the existence of organizational and technical infrastructural capabilities that facilitate the usage of the new information system (Venkatesh et al., 2003). Verkijika (2018) examined and validated the influence of facilitating conditions on the behavioral intention of the customers towards m-Commerce acceptance. However, if customers have a sufficient level of organizational, technical facilities, infrastructural and human supports while using mHealth apps, they are more likely to accept this technology. Likewise, another study testing health technology acceptance reported that the enhancement of FCs' impact on BI to adopt telehealth/eHealth/mHealth services (Kijsanayotin et al., 2009). Bhattacherjee and Hikmet (2008) ensured the vital role of infrastructural and organizational support on the acceptance of the health information system. A research conducted by Boontarig et al. (2012) explored the positive impact of FCs on behavioral intention and actual usage behavior of Smartphone for healthcare services. But it was focused on Smartphone usage of elderly people for healthcare services. However, users having better knowledge and skills of technological know-how for the apps are more likely to keep using them (Yuan et al., 2015). Therefore, the following statement was hypothesized:

H8a: FC positively influences the behavioral intention to use mHealth apps.

H8b: FC positively influences the actual usage behavior (AUB) of mHealth apps.

3.9 Lifestyle (LS)

According to Peter and Olson (1996), LS is defined as the distinct manner or way of living of individuals, including their activities, opinions and interests. A study shows that lifestyle is directly or indirectly antecedents of users' behavioral intention to adopt high-tech services (Lee et al., 2009). The high compatibility with the lifestyle of an individual makes it the most rapidly adopted technology in human behavior history. When the service delivery channel is not well-suited with the lifestyle requirement of the customer, it is less likely to succeed in offering services which will lead to customer's avoidance from using that services (Hanafizadeh et al., 2014a). Giving full consideration for lifestyle improvement, mHealth apps play a significant impact on the actual usage behavior of adopters who form a continuance usage intention of mHealth. However, health behavior changes and long time lifestyle improvement require sustainable continuity of mHealth apps (Leung and Chen, 2019). Therefore, the following hypothesis was posited:

H9a: LS positively influences the behavioral intention to use mHealth apps.

H9b: LS positively influences the actual usage behavior of mHealth apps.

3.10 Self-Efficacy (SE)

SE refers to the individual's technical skills or knowledge of accomplishing a proper task by using electronic devices such as Smartphone, wireless technologies, which in turn, impel him/her to use it continuously (Hsu and Chiu, 2004). Contemporary studies demonstrated the direct or indirect role of self-efficacy affecting intention to adopt mobile apps and other eServices etc (Alalwan et al., 2016). Similarly, Fox and Connolly (2018) found the positive association of self-efficacy with the mHealth adoption intentions. But they have focused on older adults by utilizing PMT and SCT theory. However, Self-efficacy plays a vital role in impacting the individuals' acceptance of mHealth services (Zhang et al., 2017). Therefore, the following statement was posited:

H10a: SE positively influences the behavioral intention to use mHealth apps.

H10b: SE positively influences the actual usage behavior of mHealth apps.

3.11 Trust (TR)

According to Moorman et al. (1993), TR refers to the willingness of an individual to depend on an exchange partner to whom he/she has confidence over sharing personal information. In the context of healthcare decision, trust is undoubtedly a strong influential factor. By providing competitive advantages in the services industry, the positive impact of trust in the digital age has gained support from previous researchers, practitioners and scholars (Ozawa and Sripad, 2013). Trust has also been identified as the most important variable in the acceptance of eHealth/mHealth. Therefore, for mHealth services, trust regarding data analysis and monitoring significantly affects the adoption behavior (Wu et al., 2011). For mHealth usage, we would expect that trust is more likely to influence user intention to use mHealth apps (Schnall et al., 2015). If consumers trust the authentication of this revolutionary healthcare system, it will expand their perception of the usefulness of mHealth services (Shareef et al., 2014). Hence, the following hypothesis was posited:

H11a: TR positively influences the behavioral intention to use mHealth apps.

H11b: TR positively influences the actual usage behavior of mHealth apps.

3.12 Behavioral Intention (BI)

BI is described as the extent to one deliberately intents to carry out a given action (Islam et al., 2013). Behavioral intention is positively associated with the actual usage behavior of customers. BI is the strongest determinant of the actual usage behavior of IT/IS in the healthcare domain (Turner et al., 2010). So, the following statement was hypothesized:

H12: BI positively influences the actual usage behavior of mHealth apps.

The extended research model is shown in Figure 1.

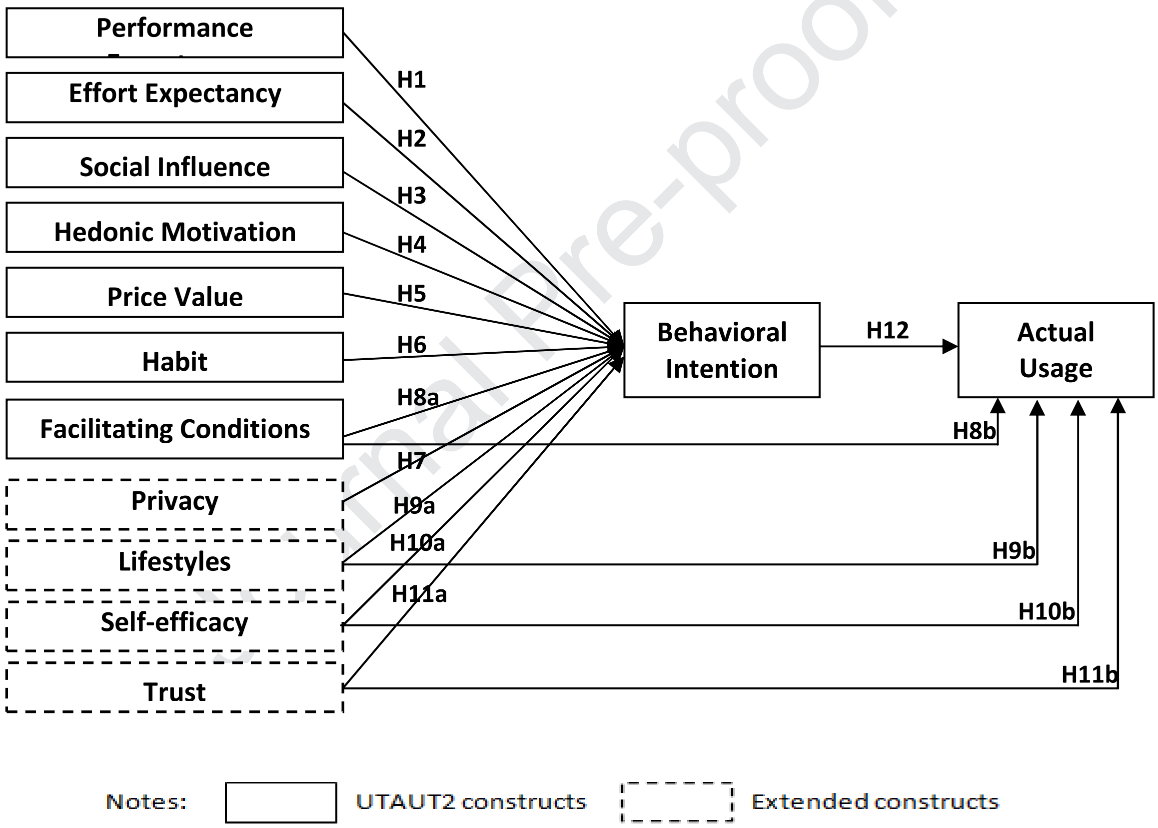

Figure 1 Research model (extension of UTAUT2 model)

4. Research Design and Methods

This part presents the methodology used to carry out the current research and validate the research model proposed in section 3. The research philosophy of this study is positivism where quantifiable/testable hypotheses were developed to be tested and validated. Since research objectives and hypotheses have been developed based on existing theory or knowledge, so, the deductive approach has been followed in the current study. As deduction requires a relatively large sample size for a systematic collection of quantitative data to perform the statistical test to generalize the findings, therefore the survey is the best method to achieve this target (Saunders, 2011).

4.1 Target Population

The mHealth apps users among the booming young generation were the target population in the context of Bangladesh, focusing on the reasons that they could provide better in-depth insights behind the adoption of mHealth apps. Unfortunately, the young generation has been suffering more from different types of preventive communicable or non-communicable diseases which in turn lead to poor quality of life due to their indiscipline life, modern lifestyles, anxiety, depression, academic pressure, family pressure, career planning, unemployment and socio-economic environment. Moreover, this technology prone generation usually lives in digital age with limited access to the basic healthcare services. Over the last 20 years, students have also been included as respondents in IS research (Compeau et al., 2012). Furthermore, these students are from different regions, religions, races, cultural backgrounds and different divisions of the entire country. Thus it is rational to assume the representation of the entire population.

4.2 Measures

To ensure the content validity of the scales, the items selected must represent the concept about which generalizations are to be made. Therefore, items selected for the constructs were mainly adapted from previous studies and modified to fit mHealth apps adoption in the context of Bangladesh (see Appendix A). Furthermore, review of the literature, discussions with researchers, academicians, mHealth apps users, medical IT experts and personal experiences have also assisted in generating items of the scale. The similar scale items employed by Venkatesh et al. (2012) to develop UTAUT2 model: PE, EE, SI, FC, HM, PV, HT, BI and AUB have been adapted in the current study which was tested and validated by prior IS/IT related studies. Whereas, scale items for TR were derived from Gefen et al. (2003); items for PR were derived from Chellappa and Pavlou (2002); items for LS were extracted from Hanafizadeh et al. (2014a) & Hanafizadeh et al. (2014b), and finally, items for SE were derived from Johnston and Warkentin (2010) and Venkatesh and Bala (2008). However, several items were adjusted according to the context of mHealth apps in Bangladesh for expression accuracy.

4.3 Questionnaire Design and Data Collection

Our study adopted the survey method, which was administered by a team of three well-trained interviewers over a period of five weeks. The questionnaires were personally distributed by the interviewers, and the respondents were made aware of their rights to withdraw participation at any time during the study period. However, due to the lack of a trustworthy list or directories of users of mHealth apps, a widely accepted convenience sampling method was employed to collect the required data. Due to the cost effective nature, this sampling method is broadly utilized in the IS research (Ruhl, 2004). Practically, mHealth apps users were reached by approaching in their respective workplaces or existing students in several largest Public and Private universities at Dhaka city, the capital of Bangladesh. The respondents were given assurance that their anonymity would be strictly maintained and the findings would be presented only in aggregate format. Next, the participants' intention to use mHealth apps and posed multiple observed statements under each latent variable were searched, utilizing five point Likert scales ranging from strongly agree (5) to strongly disagree (1). However, the questionnaire is divided into two separate parts; the first part incorporated demographic profiles, i.e. age, gender, education level, mHealth apps usage experience and mobile phone usage experience, whereas, the second part represented statements on the items of each latent construct in the proposed model.

Additionally, to ensure a high degree of reliability and validity, a pilot study was being conducted over 20 participants, including apps developers, academicians, mHealth apps users and researchers. It is evidenced in the existing literature that sample size of 12 (Julious, 2005) or even 10 (Nieswiadomy, 2002) is enough to conduct a pilot study.

The most important change was made in the items of facilitating conditions (FC) which were taken from Venkatesh et al. (2003), and modified an item for FCs to better reflect the measured constructs. The majority of the participants confirmed the appropriateness and simplicity of the language used and finally, minor changes were adjusted accordingly. Based on the results of the pretest, finally, 48 items that best fit the adoption intention and use constructs were retained.

All respondents were given consent forms and information sheets, which explained the purpose of the study. To avoid the overclaim usage of the respondents, they were given flexible time to fill in the questionnaire. The respondents were also made aware of their rights to withdraw participation at any time during the study period. To avoid potential biases, no gifts or incentives were given to the respondents, and all were voluntary participants.

Informed written consent was also obtained from all study participants, and confidentiality and anonymity were ensured in this study.

A notable variation in the opinions is found in the literature regarding the selection of proper sample size for various types of statistical analyses (Hair et al., 1998). Such as a sample size of 200 is considered as fair and 300 as good for statistical analysis using structural equation modeling (SEM) (Kline, 2015). Indeed, 450 questionnaires were randomly distributed to obtain the necessary data; yet 419 (response rate 93.11%) filled questionnaires were returned. We deleted the questionnaires with incomplete or missing data, and finally, 400 were found to be valid for further analysis. It shall be noted that the sample size of 400 is more than ten-fold that of the arrows directed to an endogenous variable and therefore is adequate for PLS analysis (Hair et al., 2011).

4.5 Data Analysis Strategy

To overcome the limitations of covariance-based SEM concerning properties of distribution, size of the sample, the complexity of the model, measurement level, identification and factor indeterminacy, as such, component based SEM (PLS path modeling) was decided to use in this study. In fact, covariance-based SEM is usually used with an objective of model validation and requires a large sample size (Tenenhaus, 2008).

In the arena of SEM approaches, CB-SEM (like AMOS, LISREL, etc.) is suitable if the aim of the study is theory testing, whereas VB-SEM (like SmartPLS, PLS-Graph. etc.) is suitable for theory developing and predicting the relationships (Hew & Kadir, 2017). Moreover, VB-SEM can deal with a complex model (6+ constructs and/or 50+ items) (Hair et al., 2017). Our study examines the determining factors of behavioral intention and use of mHealth. Since PLS is the prediction oriented SEM approach and can deal with model complexity, this technique is most suited to our analysis.

Artificial Neural Network (ANN) was used to verify the determinants of user behavioral intentions towards mHealth services. Besides, ANN was also used to rank the relative importance of the predictors derived from SEM. The ANN model can recognize non-linear and non-compensatory relationships which cannot be detected by PLS-SEM (Leong et al., 2020). However, ANN is robust against violations of multivariate assumptions and can detect both linear and nonlinear associations (Leong et al., 2019). Therefore, the novel approach has also provided robustness against noise and enhanced predictive power of the model.

5. Data Analysis and Results

5.1 Demographic Characteristics

Out of 400 valid respondents, about 60 of the respondents were male followed by 40% female presented in table 2. Besides, more than 50% of the participants were noted to be within the age range of 25-35 (52%) followed by the range of ages 18-24 years (48%). Major portions of the respondents mostly have a bachelor degree (55%) followed by post-graduate (45%). Experiences of using mHealth apps were at least 1 to 2 years (52%), whereas the experiences of using mobile phone were more than 5 years (64%).

Table 2 Participants' description (n=400)

Variables/Dimensions	Frequency	%	Variables/Dimensions	Frequency	%
Gender			*Experiences in Using mHealth apps*		
Male	241	60	1 to 2 years	209	52
Female	159	40	3 to 5 years	157	39
Age			5+ years	34	09
18-24	193	48	*Experiences in using Mobile phone*		
25- 35	207	52	1 to 5 years	144	36
Level of education			6 to 10 years	246	62
Graduate/Bachelor	221	55	11^{+} years	10	02
Postgraduate and Above	179	45			

5.2 Multivariate Diagnostic Tests

To prepare the data for structural equation modeling (SEM), multivariate diagnostic tests are the requirements for the analysis of SEM. Hair et al. (2010) confirm the multivariate assumptions when there is no existence of data outliers and no multi-collinearity problem, linearity and normality of distribution as well as a satisfactory sample size. However, in the current study, no outlier was detected since all Mahalanobis- D squared distances (D^2) were within the threshold level. The Variance Inflation Factor (VIF) and their tolerance level were assessed to detect the multi-collinearity problem among the latent variables. Kline (2005) recommended VIF values for not more than 10 and its tolerance value not less than 0.10. Referring to table 6, statistical results assured that all values of VIF and its tolerance level were observed to be within the acceptable range, which ensures the non-existence of multicollinearity problem among the latent constructs. In the normality test, all values of skewness were found within acceptance range of cut-off point of less than 3.00 as well as all kurtosis values were found to be not more than 8.00 recommended by Kline (2015). Therefore, it is clearly confirmed the normality of the data set.

5.2.1 Testing for the Common Method Bias (CMB)

There is a concerning issue that often arises among researchers who conduct studies with self-report, single-source and cross-sectional designs, known as common method bias. An investigation of Harman's single-factor with nine constructs (PE, EE, SI, FC, HM, PV, HT, TR, PR, LS, SE, BI and AUB) and 48 items of the scale was conducted as suggested by Harman (1976) and Podsakoff et al. (2003). However, there was no single factor that evolved as the first construct to be accounted for 31.915% of variance which shows less than the cut-off point of 50% as recommended by Podsakoff et al. (2003). Finally, it can be concluded that the CMB issue does not exist in the data set.

5.2.2 Linearity Test

ANOVA test was carried out to check the linear associations between the hypothesized independent and dependent variables as guided by Leong et al. (2019). It (see Appendix-B) illustrates that PV has only a non-linear association and SE has only a linear association with BI. The remaining predictors (PE, EE, SI, FC, HM, HT, LS, PR, and TR) have both non-linear as well as linear associations with BI. Besides, LS has only a linear association with AUB. The rest of the predictors (FC, SE, TR, and BI) of AUB are linearly as well as non-linearly associated.

5.3 Measurement Model

In the current study, a two-step approach consisting of a measurement model and a structural equation model (SEM) was utilized for data analysis which was suggested by Anderson and Gerbing (1988). Initially, an exploratory factor analysis (EFA) was performed due to verification of the independency and distinctiveness of the latent variables, and it has been observed that the KMO measure (0.973) and Bartlett's test (p-value 0.00) proved the appropriateness of our data for factor analysis.

In table 3, as it can be seen that all the proposed constructs have Cronbach's alpha and composite reliability values of more than 0.8628 and 0.9154 respectively, which are within the acceptance range of more than 0.7 suggested by Fornell and Larcker (1981). So, it can be assured the adequate reliability of all latent variables in the model. In Table 3, the AVE values are observed ranging from 0.730 to 0.836, whereas the estimated item loadings ranged under all variables are observed ranging from 0.8301 to 0.9945 which fall within the acceptance level (0.50) suggested by Hair et al. (2010). Therefore, conditions for convergent validity requirement are satisfactory.

Table 3 Convergent validity and internal consistency reliability

Constructs	Items	Items loadings	Mean	SD	AVE	Composite Reliability	R Square	Cronbachs Alpha
AUB	AUB1	0.8537	4.1006	0.78362	0.7562	0.9254	0.8137	0.8924
	AUB2	0.8515						
	AUB3	0.8725						
	AUB4	0.8998						
BI	BI1	0.8937	4.1217	0.78816	0.7881	0.9178	0.8359	0.8656
	BI2	0.8901						
	BI3	0.8795						
EE	EE1	0.9023	3.8438	0.96002	0.8113	0.9450	-	0.9223
	EE2	0.8749						
	EE3	0.9232						
	EE4	0.9018						
FC	EE1	0.8660	3.9744	0.78388	0.7371	0.9181	-	0.8811
	FC2	0.8470						
	FC3	0.8590						
	FC4	0.8620						
HM	HM1	0.8888	3.9683	0.83544	0.7986	0.9225	-	0.8739
	HM2	0.8896						
	HM3	0.9025						
HT	HT1	0.8719	3.9188	0.87500	0.7769	0.9330	-	0.9043
	HT2	0.8719						
	HT3	0.8854						
	HT4	0.8962						
LS	LS1	0.8809	4.0556	0.83445	0.7582	0.9262	-	0.8936
	LS2	0.8474						
	LS3	0.8810						
	LS4	0.8733						
PE	PE1	0.8852	3.7606	0.88925	0.7568	0.9256	-	0.8928
	PE2	0.8466						
	PE3	0.8621						
	PE4	0.8852						
PR	PR1	0.8917	3.9942	0.84084	0.7847	0.9162	-	0.8628
	PR2	0.8905						
	PR3	0.8752						
PV	PV1	0.9945	3.2692	1.20245	0.8359	0.9383	-	0.9379
	PV2	0.8301						
	PV3	0.9109						
SE	SE1	0.8652	4.0463	0.84110	0.7589	0.9264	-	0.8941
	SE2	0.8596						
	SE3	0.8781						
	SE4	0.8814						
SI	SI1	0.8570	3.8925	0.82376	0.7557	0.9252	-	0.8922
	SI2	0.8649						
	SI3	0.8845						
	SI4	0.8706						
TR	TR1	0.8499	3.9981	0.79992	0.7300	0.9154	-	0.8767
	TR2	0.8412						
	TR3	0.8707						
	TR4	0.8557						

Table 4 illustrates that the calculated square root of AVE was greater than the corresponding correlation among the constructs, confirming the discriminant validity. Moreover, as the most robust technique in PLS-SEM to confirm the discriminant validity among the constructs, we also analyzed Henseler et al.(2015) suggested Heterotrait-Monotrait (HTMT) ratio of correlations. Since, all the correlated values in Table 5 are below 0.90 (Gold et al., 2001), so, discrimination among the constructs is established.

Table 4 Correlation matrix and square root of the Average Variance Extracted (AVE)

	AUB	BI	EE	FC	HM	HT	LS	PE	PR	PV	SE	SI	TR
AUB	**0.869**												
BI	0.791	**0.887**											
EE	0.762	0.792	**0.900**										
FC	0.811	0.805	0.767	**0.858**									
HM	0.712	0.753	0.702	0.718	**0.893**								
HT	0.673	0.678	0.673	0.713	0.598	**0.881**							
LS	0.782	0.813	0.744	0.719	0.714	0.684	**0.877**						
PE	0.595	0.644	0.582	0.594	0.530	0.537	0.616	**0.869**					
PR	0.773	0.794	0.696	0.749	0.708	0.622	0.794	0.566	**0.885**				
PV	-0.012	-0.051	-0.040	-0.027	-0.054	-0.037	-0.053	0.001	-0.032	**0.914**			
SE	0.815	0.804	0.783	0.808	0.741	0.688	0.809	0.622	0.803	-0.019	**0.871**		
SI	0.759	0.800	0.800	0.766	0.707	0.677	0.765	0.606	0.705	-0.035	0.762	**0.869**	
TR	0.801	0.819	0.723	0.782	0.681	0.660	0.780	0.617	0.752	-0.033	0.810	0.745	**0.854**

Note: PE =Performance Expectancy, EE = Effort Expectancy, SI = Social Influence, FC = Facilitating Condition, PR = Privacy; TR = Trust, LS= Lifestyles, SE = Self-efficacy, HM = Hedonic Motivation, HT= Habit, PV= Price Value, AUB = Actual Usage Behavior & BI = Behavioral Intention.

Table 5 Discriminant validity (HTMT)

	AUB	BI	EE	FC	HM	HT	LS	PE	PR	PV	SE	SI	TR
AUB													
BI	0.895												
EE	0.839	0.886											
FC	0.887	0.894	0.851										
HM	0.806	0.866	0.781	0.818									
HT	0.748	0.766	0.736	0.798	0.673								
LS	0.882	0.896	0.820	0.880	0.808	0.761							
PE	0.666	0.732	0.642	0.670	0.599	0.598	0.690						
PR	0.881	0.874	0.780	0.859	0.816	0.705	0.883	0.645					
PV	0.046	0.037	0.037	0.035	0.048	0.056	0.047	0.038	0.044				
SE	0.891	0.897	0.862	0.888	0.838	0.765	0.898	0.697	0.882	0.045			
SI	0.850	0.879	0.873	0.863	0.801	0.753	0.857	0.679	0.803	0.050	0.853		
TR	0.893	0.881	0.805	0.890	0.778	0.740	0.881	0.698	0.865	0.022	0.897	0.842	

Note: PE =Performance Expectancy, EE = Effort Expectancy, SI = Social Influence, FC = Facilitating Condition, PR = Privacy; TR = Trust, LS= Lifestyles, SE = Self-efficacy, HM = Hedonic Motivation, HT= Habit, PV= Price Value, AUB = Actual Usage Behavior & BI = Behavioral Intention

5.4 Structural Model

The widely accepted statistical software known as Smart PLS 3.0 was applied to examine the structural path coefficients and the R-square values of endogenous constructs which tested and validated the explanatory power of a proposed model. Moreover, the bootstrapping technique, which is relatively new to the field of the statistic, was employed to test the hypotheses. Such kinds of significance were extracted by running with 5000 samples and no sign changes (see Table 6).

The figure 2 represents the results of structural equation modeling (SEM) and hypotheses testing are shown in Table 6. The statistical results revealed that the association between PE and BI (t=2.0193, β=0.0906, p<.05), SI and BI (t=2.0974, β=0.1114, p<.05), HM and BI (t=2.1979, β=0.0882, p<.05), PR and BI (t=2.1357, β=0.1015, p<.05), FC and BI (t=2.313, β=0.1537, p<.05), LS and BI (t=2.2857, β=0.1455, p<.05), SE and BI (t=2.2757, β=0.1639, p<.05), TR and BI (t=2.0034, β=0.1361, p<.05) were statistically satisfied at 5% level of significant.

Furthermore, FC and AUB (t=2.7559, β=0.1598, p<.05), LS and AUB (t=2.3203, β=0.1523, p<.05), SE and AUB (t=2.2223, β=0.2050, p<.05), TR and AUB (t=3.9568, β=0.2869, p<.05), and BI and AUB (t=2.1214, β=0.1706, p<.05), were statistically significant. Therefore, H1, H3, H4, H7, H8a, H8b, H9a, H9b, H10a, H10b, H11a, H11b & H12 were statistically supported. However, surprisingly, EE and BI (t=1.9382, β= 0.0639 and p >0.05), PV and BI (t=0.728, β= -0.017, p>0.05), and HT and BI (t=0.5583, β= - 0.0208 and p >0.05) were not significant at a level of 0.05 (p<0.05). Thus, H2, H5 & H6 were not accepted.

Table 6 Result of the hypotheses test

Hypotheses	Path	β (Co-efficient)	p-values	Tolerance Level	VIF	t-Statistics	Comments
1	PE -> BI	0.0906	0.0440	0.543	1.843	2.0193	Yes
2	EE -> BI	0.0639	0.0530	0.249	4.010	1.9382	No
3	SI -> BI	0.1114	0.0360	0.244	4.095	2.0974	Yes
4	HM -> BI	0.0882	0.0285	0.367	2.723	2.1979	Yes
5	PV -> BI	-0.0170	0.4670	0.988	1.012	0.7280	No
6	HT -> BI	-0.0208	0.5769	0.423	2.367	0.5583	No
7	PR -> BI	0.1015	0.0333	0.285	3.509	2.1357	Yes
8a	FC -> BI	0.1537	0.0212	0.238	4.195	2.3130	Yes
8b	FC -> AUB	0.1598	0.0061	0.261	3.833	2.7559	Yes
9a	LS -> BI	0.1455	0.0228	0.211	4.738	2.2857	Yes
9b	LS -> AUB	0.1523	0.0208	0.225	4.443	2.3203	Yes
10a	SE -> BI	0.1639	0.0234	0.162	6.167	2.2757	Yes
10b	SE -> AUB	0.2050	0.0268	0.173	5.771	2.2223	Yes
11a	TR -> BI	0.1361	0.0458	0.243	4.118	2.0034	Yes
11b	TR -> AUB	0.2869	0.0000	0.245	4.082	3.9568	Yes
12	BI -> AUB	0.1706	0.0345	0.188	5.328	2.1214	Yes

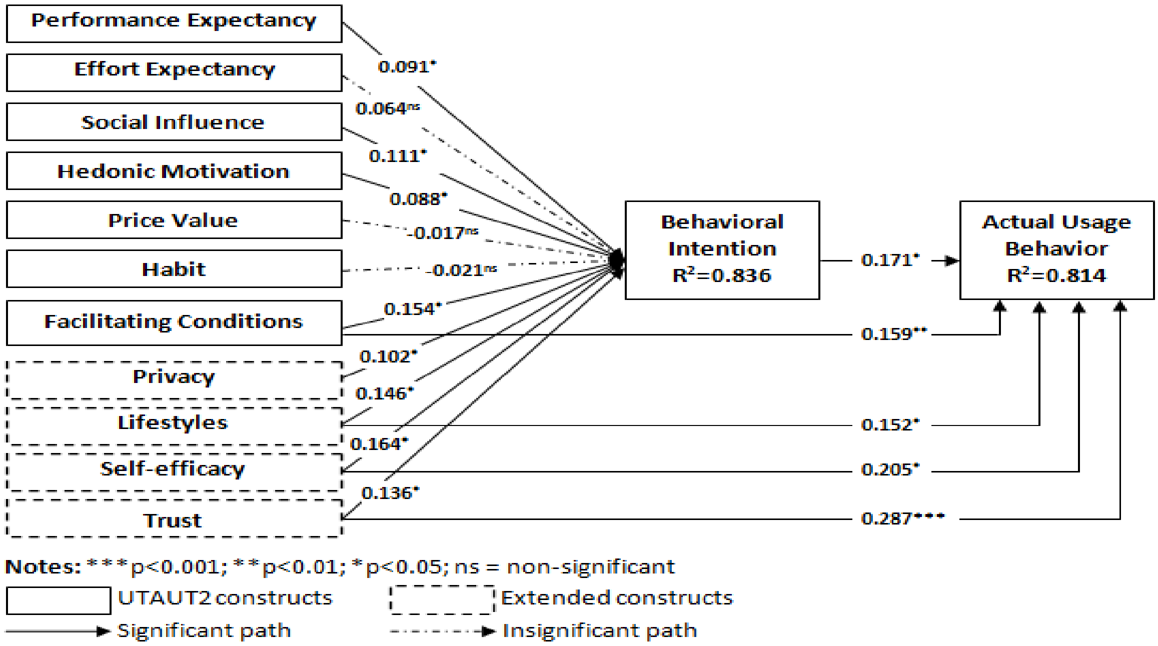

Figure 2 Extended UTAUT model with the results

5.5 Goodness of Fit (GoF)

GoF is an index recommended by Tenenhaus et al. (2004), which validated the predictive power of the proposed model as a whole. GoF estimates the average R^2 of the endogenous latent constructs and the geometric mean of the average communality. Tenenhaus et al. (2004) recommended that GoF indices usually fall in the range of 0 to 1, which are 0.10 (small), 0.25 (medium) and 0.36 (large). Unlike AMOS, PLS software does not provide global goodness of fit index. The global Goodness of Fit (GoF) of our model was calculated by the following procedures, as suggested by Tenenhaus et al. (2004).

$$\text{Goodness of Fit} = \sqrt{[(\text{average communality}) \times (\text{average } R^2)]}$$

$$= \sqrt{(0.7730 \times 0.8248)} = 0.7984$$

Therefore, from the above calculation, it has been observed that the global GoF value of our proposed model is 0.7984 which is more than cut-off point of 0.36 as suggested by Chen and Sharma (2015).

5.6 Neural Network Analysis

According to Haykin (2001), Artificial Neural Network (ANN) is defined as a particularly analogous scattered processor consisting of simple processing units having a natural predisposition for keeping storage of experimental knowledge and making it available for usage. Besides, ANN is generally a more sophisticated and mostly robust technique which provides a higher order of accuracy than conventional tools (Chong, 2013a). However, this network is similar to the human brain since it gains knowledge from its surrounding environment via the learning process. The acquired knowledge is kept in storage by the nodes or neurons, which is also known as synaptic weights (Haykin, 2001). The superiority of using this approach is that the neural network model is able to learn complex linear and non-linear relations between predictors and the adoption decision (Chan and Chong, 2012). At first, SEM is used to test the overall research model and determine significant hypothesized predictors, which are then, in a second stage, used as inputs in the neural network model to determine the relative importance of each predictor variable.

Generally, a neural network consists of three layers, i.e. input layer, hidden layer and the output layer. Data are conceived into the input layers, and the information and conclusions are generated in the output layers. Then, each input is given its own synaptic weights which are being transferred to the hidden layers. However, these values are being converted into an output value by a nonlinear activation function through applied weights.

According to Sim et al. (2014), ANN can be clustered into four different groups: i) feed forward neural networks, ii) recurrent networks, iii) multi-layer perceptron networks and iv) radial basis functional networks. Out of these models, the multi-layer perceptron neural network model was employed in the current empirical study. When utilizing the training samples to train the network, the synaptic weights of the relationships will then be adjusted through an iterative training process.

5.7 Results of Neural Network Modeling

Widely accepted statistical software SPSS 21 was employed to examine the neural network model. At this stage, the statistically significant predictors from SEM analysis were given as input into this model. There are eight numbers of factors identified as significant from SEM analysis. Hence, eight variables (08) were given as input variable in the input layers which were shown as covariates represented by significant predictors namely; PE, SI, FC, LS, HM, TR, SE and PR as illustrated in figure 3.

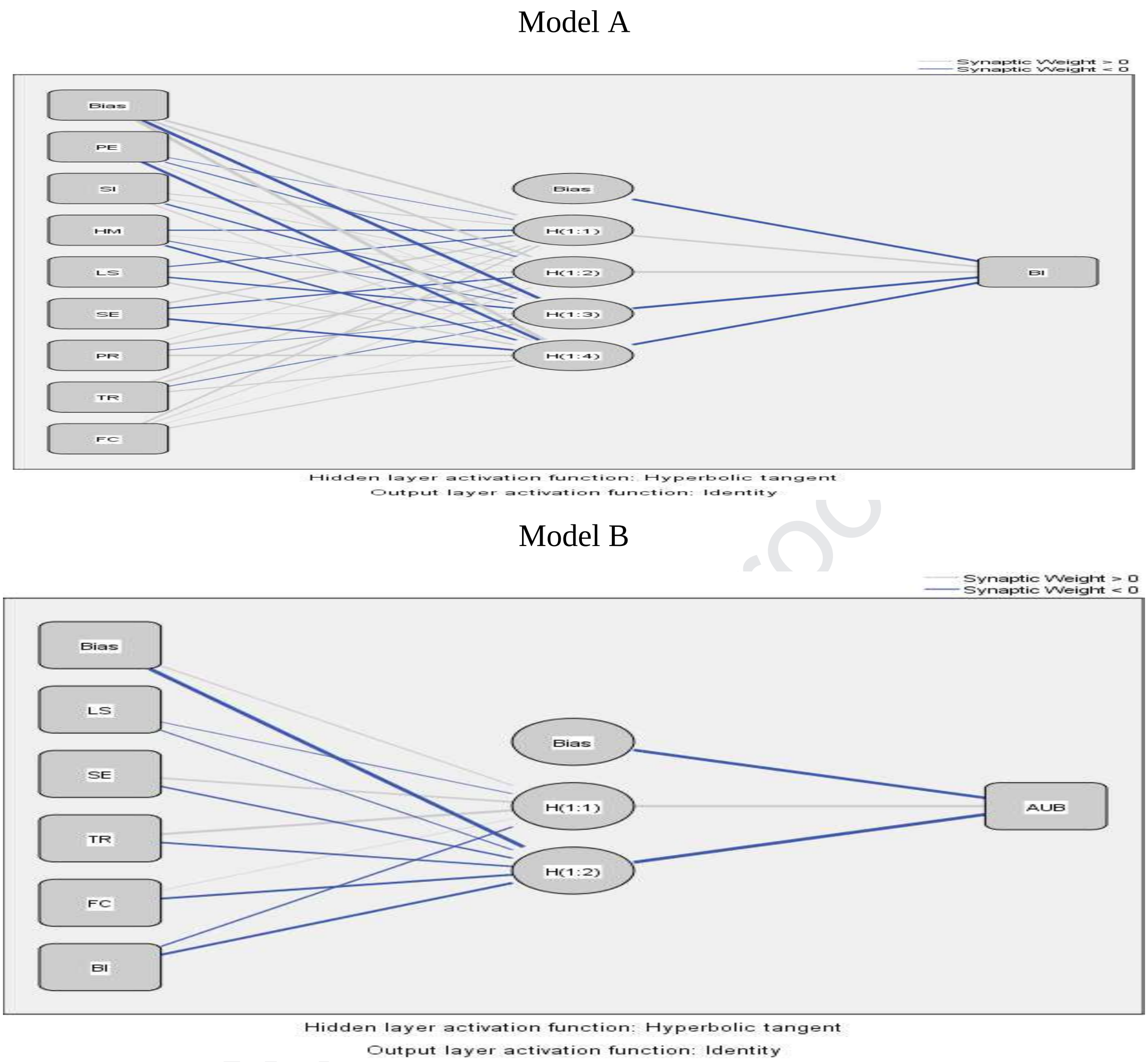

Fig. 3 Example of two ANN networks

Here, BI and AUB for mHealth apps were identified as the dependent variable in the output layer. Moreover, to overcoming the over-fitting problem of the neural network model, cross-validation tool was applied (Chong, 2013a). However, selecting a precise number of hidden neurons is still a looming challenge in the existing literature. Wang and Elhag (2007) suggested that hidden neurons or nodes should be within the range of 1 to 10 in the ANN model. At the analysis phase, 10% of data points were utilized for experiment while 90% of data points were used for training (Ooi et al., 2016; Leong et al., 2019). The RMSE values for both training and testing data points along with the mean and standard deviation are given in Table 07. The outputs indicate that in model A, the mean RMSE value for training and testing is 0.2968 and 0.2621 respectively. Likewise, in model B, the values are 0.3130 and 0.2569 for training and testing respectively. These average RMSE values are relatively small with very low standard deviations, indicating the higher order of accuracy in the statistical results (Liébana-Cabanillas et al., 2017).

The results also reveal that the extracted models are very trustworthy to capture the relationships among the significant predictors and the outputs variables. Additionally, the sensitivity analysis was calculated using the average importance of all predictors in determining a significant outcome variable. The normalized relative importance of each predictor in the model was computed by dividing the relative importance of each predictor by the highest importance predictor. Table 8 illustrates the average and normalized importance of each predictor.

Table 7 RMSE values of ANN

Network	Model A: Input; PE, SI, FC, SE, LS, TR, PR, HM and Output is BI		Model B: Input; LS, TR, SE, FC, BI and Output is AUB	
	Training	Testing	Training	Testing
ANN1	0.278243498	0.29538111	0.307096619	0.257099203
ANN2	0.311880497	0.261963738	0.301450199	0.299541316
ANN3	0.296512132	0.245356883	0.30528675	0.256320112
ANN4	0.281918034	0.261199158	0.302117527	0.262202212
ANN5	0.298305399	0.206821179	0.29240383	0.285263037
ANN6	0.313417542	0.259663243	0.311733504	0.247487373
ANN7	0.275544915	0.277758888	0.330321089	0.262202212
ANN8	0.300319275	0.258746981	0.319739477	0.241039416
ANN9	0.332941436	0.282577423	0.320589734	0.239582971
ANN10	0.279533341	0.271293199	0.339738461	0.245458754
Mean	**0.296861600**	**0.262076200**	**0.313047700**	**0.259619700**
SD	**0.018679150**	**0.024061860**	**0.014491160**	**0.019368700**

Table 8 Sensitivity analyses: normalized importance of constructs for Model A and Model B

Model A			Model B		
Variables	Average Importance	Normalized Importance	Variables	Average Importance	Normalized Importance
PE	0.081	39.500	LS	0.123	41
SI	0.144	70.240	TR	0.303	100
HM	0.205	100.000	SE	0.212	70.53
FC	0.132	64.390	FC	0.148	49.37
LS	0.091	44.390	BI	0.214	71.3
SE	0.120	58.536	-	-	-
TR	0.165	80.487	-	-	-
PR	0.037	18.049	-	-	-

However, the outcomes of the analysis of neural network model demonstrate that HM is relatively the most significant predictor of mHealth apps adoption followed by TR, SI, FC, SE, LS, PE and PR. On the other hand, trust is relatively the strongest predictor of AUB followed by BI, SE, FC and LS.

6. Discussion

In line with the research questions and objectives of this study, an empirical study was conducted using a modified UTAUT2 to gain a deeper understanding of the young generation's mHealth usages behavior in a developing country context. Along with the predictors of UTAUT2 model, four vital antecedents (PR, TR, LS and SE) were also examined. Some key findings emerged from the current study. In line with what has been discussed in the conceptual model section and proved in the result section, it could be concluded that behavioral intention and actual usage behavior was observed to reach a high level among customers with consideration of different factors.

The results of our empirical study are somewhat consistent with the existing literature on the application of UTAUT2 in mHealth apps context. The coefficient value of determination (R^2) was 83.6% and 81.4% for BI and AUB respectively which are considered strong (more than the reference value of 0.75) as recommended by Hair et al. (2011), indicating higher explanatory power of the proposed model compare to baseline UTAUT2 model that explained 74 percent and 52 percent variance in intention and use respectively (Venkatesh et al., 2012). Therefore, the study results recognized the good explanatory power of the extended UTAUT2 model for the determination of users' intention to adopt mHealth apps.

However, four original variables from UTAUT2 (i.e. PE, SI, FC, HM) and additional four variables (i.e. PR, TR, SE & LS) were proved to have a significant impact on BI and AUB of mHealth apps which are supported by Shareef et al. (2017) and Lu et al. (2009).

As expected, the role of PE on BI towards mHealth apps adoption was positively associated which was constantly in line with the current literature in technology usage contexts, such as TAM (Davis et al., 1989), TAM2 (Davis et al., 1992), and IDT (Rogers, 2010). Consequently, customers those who comprehensively use mHealth apps, are more likely to believe such healthcare delivery channel as more useful and productive in their healthcare life (Hoque and Sorwar, 2017).

Our results explored that EE was not positively associated with a person's adoption intention in the context of mHealth apps usage. This result might be due to the advancement of Smartphone interfaces in terms of navigation, and less effort is required for usage. Besides, our target respondents were well-educated young university students with adequate level of knowledge and tech oriented experiences. Thus, they are not concerned about the easiness of mHealth apps usage.

These findings are in agreement with previously tested and validated studies, i.e. (Baabdullah et al., 2019, Ahmad and Khalid, 2017, Zhou et al., 2010, Hoque and Sorwar, 2017). But this empirical finding is in opposite to the original outcome of the UTAUT2. Furthermore, BI was significantly associated with AUB, which is supported by the current literature.

Moreover, SI was identified as a strong predictor for mHealth apps adoption intention. Since the young generations are more technology and social media prone, they are more influenced by peer thoughts, opinions, and word of mouth communication regarding the usage of technology. Since the end-users may refine their behavioral intentions on information shared by the well experienced users, this finding is not surprising in this context (Rana et al., 2015, Kim et al., 2014). To put it differently, due to sensitivity of healthcare information and lack of health literacy, people in developing countries are more likely to be depended on the sources of information and suggestions derived from their social system due to lifetime threat for wrong treatment.

From the ANN analysis, it has been observed that the significant roles of intrinsic utilities, i.e. HM was proved to have a relatively strong impact on BI to use mHealth apps. Our findings in the context of mHealth apps usage are consistent with prior research (Venkatesh and Davis, 2000). Our empirical results explored that technologies which are primarily used for hedonic values (i.e. entertainment, fun and interesting features) are also important to encourage adopting mHealth apps and it is due to the inherent tech-oriented characteristics of the young participants. From the ANN analysis, TR was found to be relatively the most significant factor affecting the actual usage of mHealth apps. This, in turn, implies the important role of TR not only in influencing BI of mHealth apps users but also strongly convincing them for AUB.

Surprisingly, PV had no significant positive association with BI of mHealth apps users. This empirical result is not in agreement with the prior researches and moves against the traditional and theoretical findings, which emphasizes that the PV for the usage of healthcare service is not of paramount importance. However, this finding is supported by Koenig-Lewis et al. (2014) and Tam et al. (2018),whereas, inconsistent with the findings of the previous studies (Alalwan et al., 2017, Baabdullah et al., 2019, Yu, 2012, Rahman et al., 2019). Based on this initial experience with the trial or free version, they then determine whether or not to purchase the paid version (Whitfield, 2013). This is a typical digital business strategy for content providers (Oestreicher-Singer and Zalmanson, 2013). Although, these results may not be conventional but could be a reflection of the context of the current socio-economic environment of Bangladesh. Consequently, the factors that contribute to user intention to purchase paid apps are an important consideration for mHealth app publishers and marketers.

In the current study, the significant role of LS was found to associate with mHealth apps adoption intention and actual usage behavior which is supported by Gao et al. (2014) and Li, (2013). As the young generation leads the modern lifestyle and prefers to enjoy their life in an easy and relaxed way, they are more likely to adopt entertainment-oriented technologies. Furthermore, SE was identified as an influential factor for mHealth adoption intention and actual usage behavior which is consistent with Sun et al. (2013) and Zhang et al. (2017). However, users with high mobile self-efficacy will more likely to perceive mHealth services as being easy and relaxed to use.

Besides, it can be generally argued that TR is a prerequisite for users' acceptance of electronic health services, such as e-Health/mHealth. Therefore, TR has been tested and validated in several empirical researches relevant to IS adoption in the last couple of years (Alalwan et al., 2017, Chong, 2013b, Riffai et al., 2012) as an extension to some well-known technology adoption models/theories, i.e. TAM and UTAUT. However, our findings confirm the positive role of TR on the patients' BI to adopt mHealth apps in the context of Bangladeshi, which is supported by Tung et al. (2008).

Moreover, PR was also observed to be positively associated with mHealth apps adoption, which is supported by Wilkowska and Ziefle (2011), but not aligned with the study of Hoque et al. (2017). Due to the sensitivity and embarrassment of disclosure of personal health information, PR plays a vital role in accepting the mHealth apps among the booming Bangladeshi young generation.

In contrast, the statistical results derived from the ANN approach were slightly different and the ranked orders of the variables from higher to lower significance are as follows: HM, TR, SI, FC, SE, LS, PE and PR. Perhaps, the reasons of such changes in the ranking of predictors in terms of influencing strength in the two models are due to the nature of the relationship. Although the extended UTAUT2 model was explained quite well by the regression model given that majority of the variables are significant, the neural network analysis has a better model fit, and was able to capture both the linear and non-linear relationships between the predictors and mHealth adoption.

In summary, the results demonstrate that young generation is very much conscious regarding the vital roles of PE, SI, FC, HM, LS, SE, PR and TR for the money they paid for technology intensive services.

Therefore, ICT policy in Bangladesh is positioned favorably to implement mHealth apps to all citizens due to overcome the limitations of healthcare resources as a part of ensuring healthcare services for all. However, Bangladesh has a population of 164 million, out of them, the largest portion of them are the young generation, i.e. 96 million are <30 years old (BBS, 2018). Hence, it is clearly indicated that the young generation in this country is the future force to a greater extent because of their size, literacy rate and exposure to changing new age global technology.

6.1. Contribution to Theory

Theoretically, this research has contributed significantly in the arena of healthcare IT adoption research in a developing country. With the inclusion of four additional variables, i.e. PR, LS, TR and SE alongside the basic components of UTAUT2 and by proposing some new causal path relationship among the main determinants of BI and AUB (LS→BI, LS→AUB, TR→BI, TR→AUB, SE→BI, SE→AUB and FC→AUB), this empirical study moves beyond the path relationship what Venkatesh et al. (2012) suggested in the basic UTAUT2 model that have been disregarded in the earlier literature. On the other hand, EE → BI, PV → BI and HT → BI were insignificant in the context of mHealth apps adoption intention.

It produces new quantitative knowledge about the factors that influence the usage of mHealth apps in developing country context. However, the enclosure of four new components with the UTAUT2 is distinct in the review of the literature till to date; particularly, such integration is rare in the context of resources constrained country like Bangladesh. Besides, this study identifies the key influential drivers that are especially specific to this kind of environmental settings in a developing country context. This study got reliable findings which can be generalized to the targeted population. Moreover, this research develops the present theory-based adoption research which explores the main variables affecting BI and AUB. In contrast, researches addressing lifestyle affairs have mostly been carried out in the developed country context. To our best knowledge, so far no study took the initiative to incorporate the lifestyles into UTAUT2 model in explaining the usage of mHealth in the developing country context. Therefore, this empirical research tries to fill up the theoretical research gap with this new extended model by testing and validating with the help of innovation in the methodology of two approaches - structural equation modeling (SEM) and artificial neural network (ANN) model.

6.2. Implications for Practice

Besides these theoretical contributions to the field of mHealth literature, these findings may also present vital information for the development of policies and guidelines that will become very helpful for the implementation of mHealth apps successfully in a developing country context. The acquired information can be used by healthcare service providers, top management, policy makers and cell phone operators to promote the usage of mHealth apps.

Based on the key findings, the roles of PE, SI, FC, HM, LS, SE, TR and PR should be considered by the policy makers in promoting the intention to use mHealth apps. Indeed, it is highly required to focus primarily on the role of HM & TR, which have the highest level of influences over mHealth usage intention in Bangladesh. mHealth apps providers should concentrate on increasing words-of-mouth communication, the entertainment, operational features, compatibility with lifestyles of the users, apps self-efficacy, building trust and maintaining privacy as antecedents for maximizing the acceptance of mHealth apps.

However, the role of PE over mHealth apps should also be concerning issues for the mHealth services providers. Thus, there is a need to design mHealth solutions (mHealth devices and applications) in a way that is convenient for the users to minimize the prospects of non-adoption.

Additionally, FC should also be implemented to raise the level of personal customization in mHealth services. Therefore, managers should enhance the infrastructural facilities and other necessary resources which make users more convenient for mHealth adoption among the young generation in Bangladeshi context.

Furthermore, the role of SI over mHealth apps adoption should be concentrated by the service providers. In other words, mHealth providers are encouraged to emphasize interpersonal words-of-mouth and put more advertising on emerging social media than traditional mass media to increase the penetration of mHealth apps. Moreover, using mHealth apps services should necessarily be harmonious with the lifestyle of the end-users.

To increase the acceptability of mHealth apps, the authorities should especially employ training and promotion approaches to develop the reliability of the system, which in turn influences the adoption of mHealth services. Besides, the mHealth service providers consider the role of self-efficacy to increase the intention of mHealth apps users. They should also arrange some campaign which enhances the self-efficacy of the end-users. Therefore, mHealth apps service providers can design their services as new revenue sources in the highly stagnant ICT industries.

7. Conclusion, Limitations and Directions for Future Research

In the age of digital transformation in the healthcare industry, mHealth is one of the latest innovations in the new age technological environment over the last couple of years. So, a research initiative has been commenced to understand clearly the key influential factors that could exist behind the behavioral intention of mHealth apps in Bangladesh. Due to the lower adoption rate among the technology prone young generation, the importance of understanding and examining key determinants of mHealth apps adoption were realized recently. For this, an extended model is created based on widely accepted UTAUT2, which has higher predictive and explanatory power for accepting technology in comparison to other competing models. Moreover, the highest mobile phone penetration rate has provided a wonderful and new business prospect for health service providers as well as cell phone operators to deliver their services at quality, affordable, quality, equitable, and accessible in developing countries etc.

Furthermore, this study confirmed the roles of LS, TR, SE and PR for the adoption intention of mHealth apps in the current socio-economic context of Bangladesh. In the first phase of the analysis, structural equation modeling (SEM) was utilized to test and validate the proposed relationships, and in the second phase, ANN model was utilized to rank predictors based on the significance. To achieve greater acceptance of mHealth apps services, an effective outline is needed to be set, which will be followed by all levels of healthcare providers. Moreover, the initiatives of mHealth apps development need to be incorporated into the national healthcare scheme and should be given top priorities to fit into the healthcare infrastructure. Besides, public-private partnerships between government and community health workers along with the collaboration of private and public hospitals are considered as prerequisites for the successful implementations of mHealth apps.

Despite the theoretical and practical contributions derived from this study, a substantial number of limitations exist in this study that might restrict the generalization of the findings. Firstly, respondents of this study have been selected mainly from Dhaka, the capital city of Bangladesh. So, a large portion of the target population remains out of the scope of this study. Future study should cover the sample from eight administrative divisions of the country. Secondly, this research only measures behavioral intentions and usage of the respondents at a single time point compared to the longitudinal study of the original UTAUT2 model. Since the perception of the young generation varies over time, a longitudinal research design might capture the true picture of the intention and use of mHealth apps among young users. Thirdly, the current study revealed that EE, PV and HT had no positive impact on customer behavioral intention, and this finding does not conform to other studies in the developing country context. Hence, future researches are encouraged to re-examine the essential role of EE, PV and HT in explaining the attitude of different age groups. Fourthly, future research is expected to conduct a mixed method study where the outputs of quantitative analyses can be validated following a qualitative interview with specialists. Fifthly, unlike the original UTAUT2 model, moderating variables on the relationships were ignored in this study to ensure the parsimony of the extended model. A future study might consider respondents' demographics as moderators on the proposed relationships in the extended model to get more insights. More extensive statistical analysis is needed to discover more interesting findings while qualitative analysis can help detect humanistic design opportunities. Finally, the proposed model can also be examined in the field of other technology intensive healthcare services, i.e. telemedicine, telehealth, telecare, electronic health (eHealth), video conferencing, and Electronic Health Record (EHR) in other cultures, rural areas, socio-economic status and religious beliefs.

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Appendix-A

List of Measurement Items for Each Construct

Constructs	Items	Measure	Sources
Performance Expectancy (PE)	PE1	I find mHealth apps useful in my life.	(Venkatesh et al., 2012); (Venkatesh et al., 2003)
	PE2	Using mHealth apps increases my chances of meeting my healthcare needs. my needs.	
	PE3	Using mHealth apps helps me in managing my daily healthcare tasks more quickly.	
	PE4	Using mHealth apps increases my productive capability to manage my health.	
Effort Expectancy (EE)	EE1	Learning how to use mHealth apps is easy for me.	(Venkatesh et al., 2012); (Venkatesh et al., 2003)
	EE2	My interaction with mHealth apps is clear and understandable.	
	EE3	I find mHealth apps easy to use.	
	EE4	It is easy for me to become skillful at using mHealth apps.	
Social Influence (SI)	SI1	People who are important to me think that I should use mHealth apps.	(Venkatesh et al., 2012); (Venkatesh et al., 2003)
	SI2	People who influence my behavior think that I should use mHealth apps.	
	SI3	People whose opinions that I value prefer that I use mHealth apps.	
	SI4	People who use mHealth apps have more prestigious in my society.	
Facilitating Condition (FC)	FC1	I have the necessary resources to use mHealth apps.	(Venkatesh et al., 2012); (Venkatesh et al., 2003)
	FC2	I have the knowledge and skills necessary to use mHealth apps.	
	FC3	mHealth apps is compatible with other technologies that I used to.	
	FC4	I can get help from others when I encounter difficulties using mHealth apps.	
Hedonic Motivation (HM)	HM1	Using mHealth apps is fun.	(Venkatesh et al., 2012);
	HM2	Using mHealth apps is enjoyable.	
	HM3	Using mHealth apps is entertaining.	
Habit (HT)	HT1	The use of mHealth apps has become a habit for me.	(Venkatesh et al., 2012);
	HT2	I am addicted to using mHealth apps.	
	HT3	Using mHealth apps would be a regular activities for me.	
	HT4	Using mHealth apps has become natural to me.	
Price Value	PV1	mHealth apps are reasonably priced.	(Venkatesh et al., 2012);
	PV2	Usually mHealth apps are a good value for the money.	
	PV3	At the current price, mHealth apps provide a good value.	
Lifestyles (LS)	LS1	Using mHealth apps would fit my lifestyle.	(Hanafizadeh et al., 2014a); (Hanafizadeh et al., 2014b)
	LS2	Using mHealth apps would fit well with how I like to do my healthcare.	
	LS3	Using mHealth apps would be compatible with most aspects of my healthcare life.	
	LS4	I enjoy having new technology in my lifestyles.	
Self-Efficacy (SE)	SEF1	It is convenient to me to use the mHealth apps.	(Johnston and Warkentin, 2010); (Venkatesh and Bala, 2008).
	SEF2	I have the capability to use the mHealth apps.	
	SEF3	I could take healthcare services using mHealth apps if there was no one around to tell what to do.	
	SEF4	I could complete a health services using mHealth apps if I had never used a system like it before.	
Privacy	PR1	I believe privacy of mHealth apps users is protected.	(Chellappa and Pavlou, 2002)
	PR2	I believe personal information stored in mHealth apps system is safe.	
	PR3	I believe mHealth apps to keep participants information secure.	
Trust (TR)	TR1	I know mHealth apps is trustworthy.	(Gefen et al., 2003)
	TR2	I know that it is not opportunistic.	
	TR3	I know that it keeps its promises to its users.	
	TR4	The content of the mHealth apps is reliable.	
Behavioral Intention (BI)	BI1	I intend to continue using mHealth apps in the future.	(Venkatesh et al., 2012);
	BI2	I will always try to use mHealth apps in my daily life.	
	BI3	I plan to continue to use mHealth apps frequently.	
Actual Usage Behavior (AUB)	AU1	mHealth apps is a pleasant experience.	(Venkatesh et al., 2012); (Moon and Kim, 2001)
	AU2	I really use mHealth apps to keep my health safe.	
	AU3	I spend a lot of time on mHealth apps.	
	AU4	I use mHealth apps on regular basis.	

Appendix- B Linearity Test

ANOVA

			Sum of squares	df	Mean square	F	Sig.
BI*PE	Between groups	(Combined)	116.228	15	7.749	22.605	0.000
		Linearity	26.168	1	26.168	76.340	0.000
		Deviation from Linearity	13.179	14	0.941	2.746	0.001
	Within groups		131.628	384	0.343		
BI*EE	Between groups	(Combined)	164.394	16	10.275	47.149	0.000
		Linearity	25.786	1	25.786	118.331	0.000
		Deviation from Linearity	9.143	15	0.610	2.797	0.000
	Within groups		83.463	383	0.218		
BI*SI	Between groups	(Combined)	168.708	15	11.247	54.567	0.000
		Linearity	32.776	1	32.776	159.018	0.000
		Deviation from Linearity	10.986	14	0.785	3.807	0.000
	Within groups		79.149	384	0.206		
BI*FC	Between groups	(Combined)	181.126	14	12.938	74.644	0.000
		Linearity	15.665	1	15.665	90.377	0.000
		Deviation from Linearity	12.222	13	0.940	5.424	0.000
	Within groups		66.730	385	0.173		
BI*HM	Between groups	(Combined)	151.998	11	13.818	55.930	0.000
		Linearity	140.754	1	140.754	569.717	0.000
		Deviation from Linearity	11.244	10	1.124	4.551	0.000
	Within groups		95.859	388	0.247		
BI*HT	Between groups	(Combined)	125.656	14	8.975	28.278	0.000
		Linearity	31.410	1	31.410	98.959	0.000
		Deviation from Linearity	11.649	13	0.896	2.823	0.001
	Within groups		122.201	385	0.317		
BI*PV	Between groups	(Combined)	16.126	12	1.344	2.244	0.010
		Linearity	.154	1	0.154	.258	0.612
		Deviation from Linearity	15.972	11	1.452	2.425	0.006
	Within groups		231.731	387	0.599		
BI*LS	Between groups	(Combined)	177.787	14	12.699	69.776	0.000
		Linearity	67.072	1	67.072	368.531	0.000
		Deviation from Linearity	5.089	13	0.391	2.151	0.011
	Within groups		70.069	385	0.182		
BI*SE	Between groups	(Combined)	184.746	14	13.196	80.502	0.000
		Linearity	59.174	1	59.174	360.984	0.000
		Deviation from Linearity	3.666	13	0.282	1.720	0.055
	Within groups		63.110	385	0.164		
BI*PR	Between groups	(Combined)	163.638	11	14.876	68.535	0.000
		Linearity	56.586	1	56.586	260.765	0.000
		Deviation from Linearity	7.051	10	0.705	3.249	0.000
	Within groups		84.219	388	0.217		
BI*TR	Between groups	(Combined)	172.650	14	12.332	63.131	0.000
		Linearity	42.931	1	42.931	219.772	0.000
		Deviation from Linearity	6.155	13	0.473	2.424	0.004
	Within groups		75.207	385	0.195		

ANOVA (Continue)

			Sum of squares	df	Mean square	F	Sig.
AUB*FC	Between groups	(Combined)	178.043	14	12.717	73.111	0.000
		Linearity	11.638	1	11.638	66.909	0.000
		Deviation from Linearity	16.572	13	1.275	7.329	0.000
	Within groups		66.969	385	0.174		
AUB*LS	Between groups	(Combined)	168.544	14	12.039	60.613	0.000
		Linearity	61.723	1	61.723	310.758	0.000
		Deviation from Linearity	4.170	13	0.321	1.615	0.078
	Within groups		76.468	385	0.199		
AUB*SE	Between groups	(Combined)	184.580	14	13.184	83.994	0.000
		Linearity	54.418	1	54.418	346.685	0.000
		Deviation from Linearity	7.394	13	0.569	3.624	0.000
	Within groups		60.432	385	0.157		
AUB*TR	Between groups	(Combined)	183.342	14	13.096	81.756	0.000
		Linearity	42.643	1	42.643	266.215	0.000
		Deviation from Linearity	9.148	13	0.704	4.393	0.000
	Within groups		61.670	385	0.160		
AUB*BI	Between groups	(Combined)	181.477	11	16.498	100.751	0.000
		Linearity	73.189	1	73.189	446.959	0.000
		Deviation from Linearity	8.288	10	0.829	5.061	0.000
	Within groups		63.535	388	0.164		

Highlights

- The focus of this study was to explore the factors influencing behavioral intention and actual usage behavior of mHealth apps.
- The conceptual model was proposed based on the extended Unified Theory of Acceptance and Use of Technology (UTAUT2) and other factors.
- The results support the significant role of self-efficacy, privacy, trust, lifestyle and some UTAUT2 factors.
- Additionally, Neural Network Model was also employed to rank relatively significant predictors obtained from SEM.
- Neural Network Model indicates the Trust and Hedonic Motivation as the most significant predictor.

CRediT Authorship Contribution Statement

Mohammad Zahedul Alam: Conceptualization, Methodology, Writing - original draft, Visualization. **Dr. Wang Hu:** Supervision, Writing-review & editing. **Md. Abdul Kaium:** Investigation, Data curation. **Dr. Md Rakibul Hoque:** Validation, Final review & editing. **Dr. Mirza Mohammad Didarul Alam:** Software & Formal analysis.