Consumer Behavior of eHealth Services

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A dissertation submitted as the partial requirement for the degree of Doctor of Philosophy

August 2018

Abstract

eHealth is considered as one of the most prominent contributions of ICT towards global healthcare. eHealth industry is growing faster than the conventional face-to-face healthcare industry. Rapid advancement and affordable access to ICT, raising health awareness, increasing middle class, and growing elderly population are fueling this global eHealth boom.

Existing studies related to eHealth are mostly focused on IT design and implementation, system architecture and infrastructural issues. However, the success of health IT doesn't only depend on its design and infrastructure but also on its consumer acceptance for whom the service is being designed and delivered. It is evident that not enough studies are conducted to explore the overall consumer behavior of eHealth, especially from the perspective of Asian developing countries where most of the worlds' population resides.

The goal of this research is to analyze and understand the consumer behavior of eHealth. To attain the overall goal, the study has identified several specific objectives stated below:

i. To explore the current level of knowledge and awareness of eHealth among rural consumers.
ii. To identify the factors that affect consumers' acceptance of eHealth and to propose an eHealth acceptance model.
iii. To measure the consumers' level of trust by assessing their compliance behavior toward e-Prescription and to identify the factors with relative magnitudes that affect the consumers' compliance behavior.
iv. To predict the consumer behavior through machine learning and to propose the best performing model in terms of predictive accuracy.

Data were collected between June and July 2016 from 592 randomly selected rural respondents through a field survey with a structured questionnaire. To attain the research goal, information related to the consumers' demography, socioeconomic status, perception and behavioral response towards eHealth systems were collected. Various statistical tools including descriptive statistics, factor analysis, reliability test, correlation and logistic regression models and machine learning algorithms were used to analyze the data.

The major findings and contributions of this research are listed below:

First, the study explored the current level of knowledge and awareness of eHealth among rural consumers. We found approximately 40% of the rural respondents have knowledge about using ICT in obtaining healthcare services while 32% have their own experience of receiving eHealth care services from PHC. The study has also identified the major reasons for using and not using PHC services.

Second, we identified the factors with their relative magnitudes that affect consumer acceptance of eHealth and proposed an extended eHealth acceptance model for rural end-users which performs slightly better (by 2%) than the existing TAM related models with an R2 of 0.54 and adjusted R2 of 0.51.

Third, we proposed a new mechanism of measuring patients' trust towards eHealth systems by assessing their e-prescription compliance behavior instead of asking simple binary or Likert scale questions. The study found 74.7% primary compliance among the users. We also found the prime factors with their relative magnitudes that affect the patients' compliance behavior.

Finally, we have developed a prediction model based on machine learning algorithms which can predict consumers' usage behavior with an accuracy of 85.9%, precision of 86.4%, recall of 90.5%, F-score of 88.1%, and AUC of 91.5% through 12 predictive variables.

The findings of this research are expected to be helpful for eHealth system developers and service providers to gain a comprehensive understanding of the factors that affect the end-users' or consumers' acceptance of remote healthcare service. Therefore, they can redesign their technologies and services in accordance with the requirements and preferences of their target consumers. As a consequence, large-scale social adoption and long-run sustainability of eHealth systems will be achieved. The findings will also help to increase the level of e-prescription compliance among rural patients, therefore the overall morbidity is expected to be reduced. Finally, the machine learning prediction model will assist the service providers to select more appropriate users and areas to be served with limited resources with a certain level of accuracy and precision.

Since the study was conducted on a particular geography, the results may raise concerns about the generalization of the findings. Further research, therefore, should be carried out covering broader geography. A few additional variables could be added to the proposed eHealth acceptance model such as compatibility, technology anxiety, and resistance to change to gain more comprehensive insights of eHealth acceptance. Consumer behavior has an ever-changing phenomenon and this is why their perceptions and attitude towards eHealth systems may change over times. It is, therefore, necessary to conduct a longitudinal or time-series study to measure the fluctuations in behavior.

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List of Abbreviations

Edu: Level of education

MFE: Monthly family expenditure

Cellph: Use of cellphone

Ad: Advertisements

SR: Social reference

PU: Perceived usefulness

PEU: Perceived ease of use

PP: Perceived privacy

PC: Perceived cost

SDT: Service delivery time

SQ: Service quality

RD: Result demonstrability

PHC: Portable Health Clinic

Chapter 1: Introduction

1.1 Background

Remote healthcare systems including eHealth, mHealth, telemedicine, telemonitoring, Electronic Health Records (EHR), Hospital Information Systems (HIS) etc. are getting attention due to the rapid advancement in information and communication technology (ICT) worldwide [1]–[3]. However, some rural and remote communities especially in developing and under-developed countries are still deprived of quality healthcare services due to the lack of necessary infrastructure, insufficiently qualified healthcare workforce and expensive access to quality healthcare [4]–[6]. In this circumstance, the concept of eHealth has been emerged and gained a good momentum. Recent studies [7]–[9] described eHealth as one of the most prominent contributions of ICT towards healthcare with noticeable positive impacts. DeLuca et al. [10] defined eHealth as an umbrella that includes a spectrum of technologies including computers, telephony, and wireless communications to provide healthcare access to remote patients, care providers, care management and educators. Oh et al. [11] defined eHealth as a process of providing medical assistance through electronic means, in particular through the Internet which includes teaching, treating, monitoring and interacting with patients as well as health professionals.

According to the Global Healthcare Industry Outlook [12], the global healthcare market size is valued USD 6.84 trillion in 2017 and is expected to reach USD 8.75 trillion by 2022 with a compound annual growth rate (CAGR) of 5.1%. Another research report [13] from Mordor Intelligence says, the global e-Health market is estimated at USD 124 billion in 2017 and is projected to reach USD 244 billion by 2022, growing at a CAGR of 14.56% during the forecast period. The statistics and predictions above clearly depict that, eHealth is growing faster than traditional healthcare services. Rapid global advancement and affordable access to information and communication technology, raising health awareness, rising income level, and growing elderly population are the key factors that are favouring this eHealth industry growth [14], [15].

Most of the existing studies related to the application of information technology (IT) in healthcare are focused on IT design and implementation, system architecture and infrastructural issues of eHealth [16]–[19]. Some described the importance eHealth in public health development including its ancillaries and barriers to mass adoption [20]–[23]. Some studies separately measured the impact of cultural factors [22], demography and socio-economic factors [6] on eHealth adoption. However, the success of health IT doesn't only depend on its design and infrastructure but also on its consumer acceptance for whom the service is being designed and delivered [24]–[26]. It is evident that not enough studies are conducted to explore the overall consumer behavior towards eHealth, especially from the perspective of Asian developing countries where most of the worlds' population resides. Therefore, it has become necessary to measure the consumers' knowledge, awareness, acceptance and compliance behavior towards eHealth in order to gain a comprehensive understanding of their overall behavior.

1.1.1 Consumer Behavior

Consumer behavior is the study of individuals, groups, or organizations and the processes they use to select, secure, use, and dispose of products, services, experiences, or ideas to satisfy needs and the impacts that these processes have on the consumer and society [27], [28]. It studies how consumers think, feel, and react towards a product or service in different situations. It also studies how the consumers are influenced by their environment and surroundings (e.g. culture, friends & family, media etc.) Understanding consumer behavior, like any other industry, has become extremely important for the healthcare industry as well. If the service providers fail to understand what consumers actually want and how they respond to a particular product, service or offer, the provider will not be able to sustain in the long-run. Consumer behavior is a complex field of study since it deals with people's psychology and each consumer has different mindset and attitude. Therefore, understanding the theories and concepts of consumer behavior will help a product, service or technology developer to make their product or technology successfully adopted by its target consumers.

1.1.2 Need for Understanding Consumer Behavior

Consumer behavior is studied to predict consumers' reaction in markets. If a producer or developer or provider of any product or service understands its customers, the likelihood of being successful in the market place usually increases. The success of any product or service is based on understanding the consumer and providing the kind of products that the consumer wants. Studying consumer behavior is very much emphasized for the following reasons:

To know the consumers' needs

Consumers respond favourably while evaluating the products that best satisfy their needs. A marketer studies how consumers spend their available resources on the consumption of related items. It includes the study of what they buy, when they buy it, where they buy it and how often they use it. So, a knowledge of consumer behavior will be of immense help to the marketer which will help to satisfy their needs. He can understand the consumer's reaction to a firm's marketing strategies. It would help in planning and implementing marketing strategies.

To understand the consumers' psychology

The study of consumer behavior enables the marketer to understand the psychology of consumers. Consumer psychology is based on his knowledge, attitude, intention and motive. The psychology of customer develops on the basis of knowledge he has. Sales promotion plays an important role to provide the knowledge of the product to consumers. Attitude is a state of mind or feeling. Attitude explains behavior. Intention means a desire to do something. A marketing program is formulated only after understanding the intention of consumers. Motive is the integral state which directs the behavior of a person.

To achieve marketing goals

The key to a company's survival, profitability, and growth in a highly competitive marketing environment is its ability to identify and satisfy unfulfilled consumer needs better and sooner than the competitors. Thus, consumer behavior helps in achieving marketing goals.

To predict market trend

Consumer behavior can also aid in projecting the future market trends. Marketer finds enough time to prepare for exploiting the emerging opportunities, and/or facing challenges and threats.

To identify consumer differentiation

Market exhibits considerable differentiation. Each segment needs and wants different products. For every segment, a separate marketing program is needed. Knowledge of consumer differentiation is a key to fit marking offers with different groups of buyers. Consumer behavior study supplies the details about consumer differentiations.

To create and retain consumers

Marketers who base their offerings on a recognition of consumer needs find a ready market for their products. The company finds it easy to sell its products. In the same way, the company, due to continuous study of consumer behavior and attempts to meet changing expectations of the buyers, can retain its consumers for a long period.

To face competition

Consumer behavior study assists in facing competition, too. Based on consumers' expectations, more competitive advantages can be offered. It is useful in improving competitive strengths of the company.

To develop new products

New product is developed in respect of needs and wants of the target market. In order to develop the best-fit product, a marketer must know adequately about the market. Thus, the study of consumer behavior is the base for developing a new product successfully.

To understand the dynamic nature of market

Consumer behavior focuses on dynamic nature of the market. It helps the manager to be dynamic, alert, and active in satisfying consumers better and sooner than competitors. Consumer behavior is indispensable to watch movements of the markets.

To ensure the effective use of productive resources

The study of consumer behavior assists the manager to make the organizational efforts consumer-oriented. It ensures an exact use of resources for achieving maximum efficiency. Each unit of resources can contribute maximum to objectives.

It is to be mentioned that the study of consumer behavior is not only important for the current sales but also helps in capturing the future market. Consumer behavior assumes: Take care of consumer needs, the consumers, in return, will take care of your needs. Most of the problems can be reasonably solved by the study of consumer behavior. Modern marketing practice is almost impossible without the study of consumer behavior.

1.1.3 eHealth Initiatives in Bangladesh

Bangladesh has a serious shortage of physicians, paramedics, nurses, and midwives. The nurse-physician ratio is one of the poorest in the world. There are approximately three physicians and one nurse per 10,000 people, the ratio of nurse to physician being only 0.4 [29]. The available qualified healthcare providers are centered in urban areas while the majority of people live in rural areas, resulting in an inequitable access to quality healthcare for the rural and disadvantaged sections of the population [30]. Under these circumstances, ICT based healthcare services i.e. mHealth and eHealth have been emerged in Bangladesh since late 90's, which provides a new opportunity to ensure access to quality healthcare services for the population in general, and for people from poorer sections and hard-to-reach areas in particular. The effectiveness of these services depends on the evidence-informed development of appropriate programs designed around people's perceptions of ICT based healthcare systems and user feedback. The application of Information and Communication Technology (ICT) to healthcare, especially e-Health, is rapidly advancing in Bangladesh. Both the public and private sectors have contributed to the development of the e-Health infrastructure throughout the country [31].

According to Reich et al. [32], access to quality health services and associated costs are threats to Bangladesh's current momentum for universal health coverage. Among many health system concerns, a serious lack and unequal distribution of qualified health human resources (HHR) is a harsh reality. Only 25% of the HHR is working for the rural population which accounts for 70% of the total population [33]. Despite impressive gains in many health indicators, recent evidence has raised concerns regarding the utilization, quality and equity of healthcare. In the context of new and unfamiliar public health challenges including high population density and rapid urbanization, eHealth is being promoted as a route to cost-effective, equitable and quality healthcare in Bangladesh [34].

The year 1998 is a milestone for e-Health in Bangladesh as the first e-Health project was launched by Swinfen Charitable, a not-for-profit institute. It involved a collaboration between the Centre for the Rehabilitation of the Paralyzed (CRP) in Bangladesh and the Royal Navy Hospital Haslar, in the UK. During the same year, the Ministry of Health and Family Welfare (MoHFW) initiated their first e-Health initiative [35]. Just a year later the Telemedicine Reference Center Limited (TRCL), a private company, initiated the use of mobile phones for healthcare delivery. In 2001, a professional coalition called Bangladesh Telemedicine Association (BTA) was established with a view to providing a platform for the ongoing and sporadic eHealth initiatives in the country. A similar platform called the Sustainable Development Network Program (SDNP) was formed in 2003, with the objective of establishing better collaboration and understanding among providers [33]. Later in 2006, TRCL paired with GrameenPhone, country's largest telecom service provider to initiate a mobile phone-based call center for subscribers called Health Line: 789. A number of NGOs including BRAC, Sajida Foundation and DNet subsequently developed an interest in eHealth. Later many private entities involved in telemedicine and/or patient record systems in their clinics and hospitals. According to a study conducted by the International Centre for Diarrhoeal Disease Research, Bangladesh (ICDDRB), till March 2012, a total of 26 initiatives (either pilot or full-scale programs) with direct or indirect associations with e-Health and/or m-Health have been taken in Bangladesh, among which four were public, eighteen private and four NGO [34].

1.1.4 Portable Health Clinic (PHC): The Experimental Field

Portable Health Clinic (PHC) is an eHealth initiative, jointly developed by Kyushu University, Japan, and Grameen Communications, Bangladesh to provide affordable healthcare solutions to low-income, low literate people living in remote and under-served communities in Bangladesh by using information and communication technologies [36], [37].

The PHC back-end comprises GramHealth software applications, database, and medical call center. GramHealth software applications process patients' Electronic Health Records (EHR) and doctor's e-Prescriptions and store them in a database. Doctors at the medical call center access GramHealth data cloud through the Internet or have a copy of the database in the call center server. Upon receiving a video call from a patient, the doctor can find patient's previous EHR, can create, and send an e-Prescription [38]. This saves doctor's time as the doctor does not need to ask questions about patient's history but can focus on the immediate health inquiry.

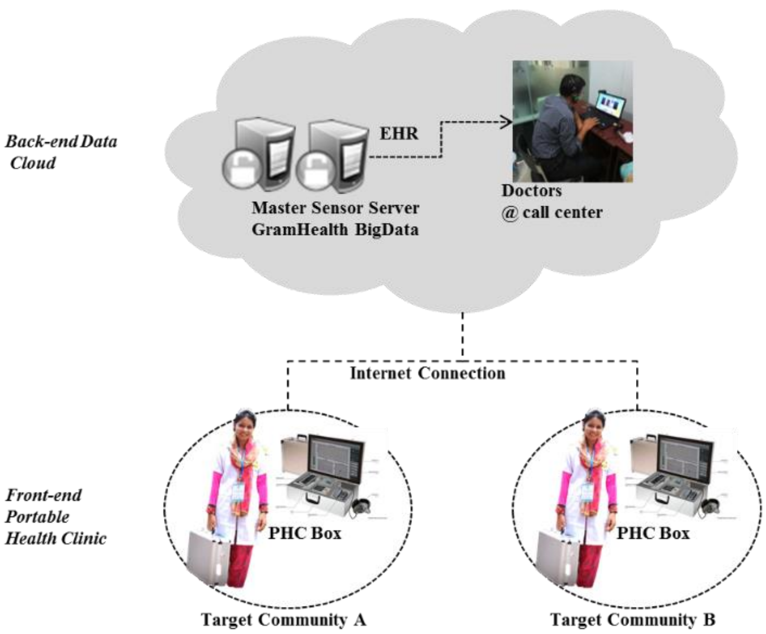


Figure 1.1 System architecture of PHC

The PHC front-end has the instances of portable briefcase consisting of medical sensors and measuring equipment operated by healthcare workers living in remote communities. The medical sensors are used to identify non-communicable diseases (NCDs). The local sensor server synchronizes its cache with the master sensor server when an Internet connection is available. The master sensor server in the back-end data cloud stores all sensor data and provides data to the GramHealth database and to the doctors in the call center [38] as depicted in Figure 1.1.

The operational steps of PHC are shown in Figure 1.2 below:

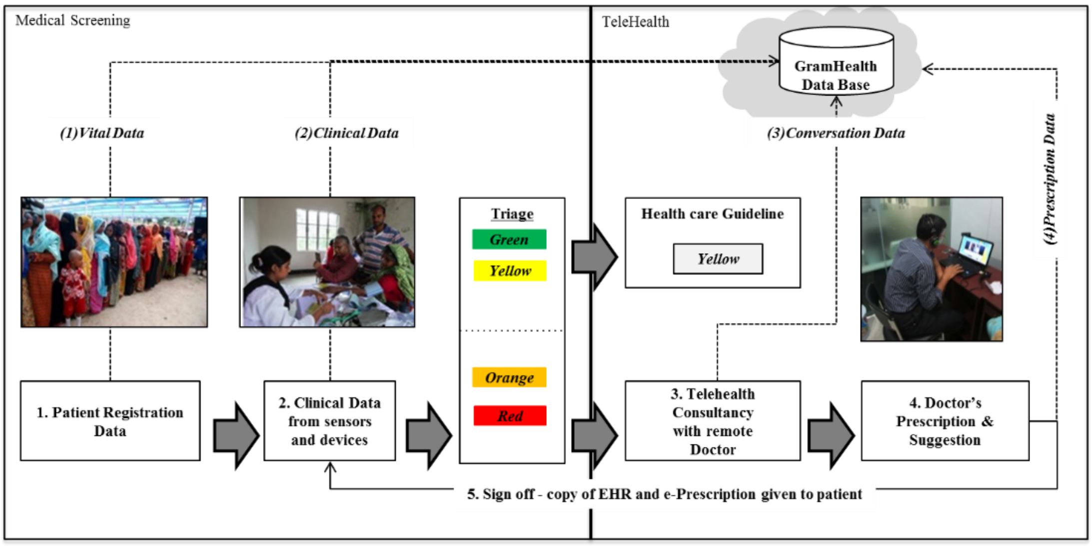


Figure 1.2 Operational steps of PHC

The five basic operational steps of PHC is described below:

1. **Registration:** A patient registers his/her vital information such as name, age, sex, location and disease complaints. A data entry operator inputs the data into the database. A patient ID is given to the patient. The patient pays for the service in advance.
2. **Health Checkup:** A healthcare worker takes the patient's physical checkup (body temperature, weight, height, BMI, Waist, Hip, Blood test, Urine test) and data is automatically sent to GramHealth server. The sensor server grades the patient according to the color-coded risk stratification: green (healthy), yellow (caution), orange (affected) and red (emergency). The "green" patients are given the health

checkup results. The “yellow” marked patients are given a health guidance booklet. The “orange” and “red” marked patients consult with a call center doctor.

3. **Telehealth consultancy:** Color coded ”orange” and ”red” marked patients talk to the call center doctor for further investigations of their disease and explanation of their medical records. Telehealth consultancy is over voice and video. The audio record is archived in the database.
4. **Prescription and lifestyle advice:** The call center doctor identifies the disease after checking the clinical data, discussing with the patient for their symptom analysis and his/her past health records, if any. The doctor then fills up the prescription and lifestyle advice and a healthcare worker helps the doctor to insert the necessary information into the database and sends to the healthcare worker.
5. **Sign off:** The healthcare worker prints and gives a copy of the Electronic Health Record and Prescription to the patient and schedules a follow-up health checkup within two months.

PHC has started its experimental service since 2010. Until January 31, 2018, it reached 32 remote locations in 9 districts and served 41,240 rural patients among which 55.2% were male and 44.8% female [39]. For our research, we selected Bheramara sub-district of Kushtia as our data collection site which is one of the above mentioned 9 Districts, located in the North-Western part of Bangladesh. PHC started serving in Bheramara from 2012 and served 4701 rural patients until the above-mentioned date.

1.2 Research Objective

The broader objective of this research is to explore and understand the consumer behavior of eHealth in developing countries, particularly PHC in Bangladesh. To attain the overall goal, the study has identified several specific objectives stated below:

i. To measure the current level of knowledge and awareness of eHealth among rural consumers.

ii. To identify the factors that affect consumers’ acceptance of eHealth and to propose an extended eHealth acceptance model.

iii. To measure the consumers' level of trust by assessing their compliance behavior toward e-Prescription and to identify the factors with relative magnitudes that affect the consumers' compliance behavior.

iv. To predict the consumer behavior through machine learning and to propose the best performing model in terms of predictive accuracy.

1.3 Major Research Contributions

The broader objective of this research was to understand the consumer behavior towards human assisted remote healthcare systems, PHC in particular. In order to achieve the research objective, we conducted a survey on 592 rural respondents including both actual and potential users of PHC. Data related to the consumers' demography, socioeconomic status, perception towards remote healthcare system and behavioral response were collected through personal interview with a structured questionnaire. Data then were analyzed through various statistical models and machine learning algorithms to attain the specific research objective.

The three major research contributions are described below:

First, this research **proposed an extended eHealth acceptance model** for rural end-users which performs slightly better (by 2%) than the existing TAM related models with an R^2 of 0.54 and adjusted R^2 of 0.51.

Second, we **proposed a new mechanism of measuring patients' trust** towards remote healthcare systems by assessing their e-prescription compliance behavior instead of asking simple binary or Likert scale questions. The study found 74.7% primary compliance among the users. We also found the prime factors with their relative magnitudes that affect the patients' compliance behavior.

Third, we have **developed a prediction model** based on machine learning algorithms which can predict consumers' usage behavior with 89.5% accuracy through 12 predictive variables.

The findings of this research are expected to be helpful for eHealth system developers and service providers to gain a comprehensive understanding of the factors that affect the end-users' or consumers' acceptance of remote healthcare service. Therefore, they can redesign their technologies and services in accordance with the requirements and preferences of their target consumers. As a consequence, large-scale social adoption and long-run sustainability of eHealth systems will be achieved. The findings will also help to increase the level of e-prescription compliance among rural patients, therefore the overall morbidity is expected to be reduced. Finally, the machine learning prediction model will assist the service providers to select more appropriate users and areas to be served with limited resources with a certain level of accuracy and precision.

1.4 Thesis Outline

Chapter 1 describes the research background along with related studies, research objectives and the major research contributions. It also gives a brief overview of eHealth initiatives in Bangladesh including Portable Health Clinic (PHC) on which this research is based.

Chapter 2 explores the current level of knowledge, perception and awareness of eHealth among rural end-users including their reasons for using and not using eHealth services from PHC.

Chapter 3 proposes an 'eHealth acceptance model' for rural consumers in developing countries after evaluating the factors that significantly affect consumers' eHealth acceptance behavior.

Chapter 4 examines the patients' compliance behavior toward e-Prescription and proposes a new mechanism of measuring trust based on action instead of response. It also evaluates factors affecting patients' compliance behavior with their relative magnitudes.

Chapter 5 develops and compares predictive models based on machine learning algorithms in order to predict consumers' usage of eHealth in advance. Finally, it proposes the best-fitted model in terms of predictive accuracy.

Chapter 6 concludes the study with its major contributions, implications of research findings, limitations and future works.

Chapter 2: Knowledge and Awareness Behavior

2.1 Background and Objective

Understanding consumer behavior of any technology-based service starts with the understanding of consumers' knowledge, awareness, perception and attitude towards that technology [40], [41]. Since eHealth services are comparatively new to the low income, low literate rural people of Bangladesh, the long-run sustainability of PHC largely depends on consumers' perception and their acceptance of this new technology. Therefore, the understanding of factors that influence technology acceptance is essential for its successful adoption [42]. Considering the commercial value of technology, technology-based services can be described as the result of a protracted industrial approach, research and development, and continuously evolving innovation plans and actions [43]. On account of technology's broadening characters in service delivery, it is necessary to comprehend consumer's readiness to the use technology-based services such as eHealth [44]. Studies investigating predictors of technology usage in services have generally focused on ease of use, usefulness, and other technical design features as well as consumer demographics and traits [45]. Although there are ample evidence and concerns pertaining to the technological perspective of e-Health, its current status, challenges and prospects, there are only a few studies conducted in regards to consumer acceptance [46]–[48]. It is therefore important to measure the current level of knowledge, awareness, perception and attitude of consumers towards eHealth systems and the system characteristics, which directly affect system acceptance once implemented [49].

The objectives of this chapter of the study are:

i. To explore the current level of knowledge, perception and understanding of existing eHealth services among rural consumers.
ii. To identify the reasons for accepting or rejecting eHealth services from PHC.

2.2 Methods

The study is exploratory [50] and quantitative in nature. Data were collected between June and July 2016 through a field survey conducted in Bheramara sub-district of Kushtia, a North-Western district of Bangladesh. PHC started serving in Bheramara from 2012 and served 4701 rural patients until January 31, 2018.

A structured questionnaire was developed initially in English, which later on, was translated into Bengali (the local language of Bangladesh). Close-ended questions were used to extract respondents' demography and a five-point Likert-scale from extremely disagree to extremely agree with a neutral point on 3 was used to extract the cognitive information. A pilot study was conducted 7 randomly selected 18+ rural inhabitants to test the understandability of the questionnaire. Their feedback was considered to review the questionnaire. To maintain the right of privacy of the respondents, they have been briefed on the research purpose and asked whether they want to participate in the survey as well allow us to use their response in our scientific publications.

A total of 592 randomly selected respondents (n = 592) were approached to collect primary data on their knowledge, understanding and awareness of eHealth. The sample was drawn by following a simple random sampling method in order to eliminate the bias by providing all individuals with an equal chance to be selected [51]. Several studies [52]–[54] related to sampling for social and behavioral science suggested to calculate the minimum required sample size for a cross-sectional study, as ours, based on population size, confidence level and margin of error. The formula is given below:

$$\text{Sample size} = \frac{\frac{z^2 \times p(1-p)}{e^2}}{1+\left(\frac{z^2 \times p(1-p)}{e^2 N}\right)}$$

Where: z = z value (e.g. 1.96 for 95% confidence level), p = percentage picking a choice, expressed as decimal (0.50 used for sample size needed), e = error margin, expressed as decimal (e.g. 0.05 for 5%) and N = population size.

According to Bangladesh National Portal [55], Bheramara, has a total population of 175,480. By considering 95% confidence level and 5% margin of error with a population (N) of 175,480, the minimum required sample (n) size is 384. This minimum required sample size has been drawn by applying the formula mentioned above and also verified with two widely used web-based statistical survey service providers namely, The Survey System [55] and Survey Monkey [56]. The sample size for this section of the study is 592 which is above the calculated minimum requirement, therefore, we considered it as an optimum number of sample size. Descriptive statistics along with frequency distribution were used to analyze consumer knowledge and awareness of eHealth.

2.3 Results

2.3.1 Respondents' Demography

Fifty-eight percent of our total respondents are male while the rest are female. The distribution of respondents by age group, level of education, and monthly family expenditure are shown in Table 2.1.

Table 2.1 Respondents' Demography [n = 592]

	Frequency	Percentage
Gender		
Male	343	58.0%
Female	249	42.0%
Age Group		
< 30 (Young)	136	23.0%
30 – 45 (Adult)	290	49.0%
46 – 60 (Mid-aged)	115	19.5%
60> (Senior)	51	8.5%

Education		
None	95	16.0%
Primary	124	21.0%
Secondary	225	38.0%
College & Higher	148	25.0%
Monthly Family Expenditure		
Less than 6000 BDT	231	39.0%
6001 - 10000 BDT	192	32.5%
10001 - 15000 BDT	118	20.0%
15001 - 20000 BDT	36	6.0%
Above 20000 BDT	15	2.5%

2.3.2 Knowledge about the Use of ICT in Healthcare

In order to explore the consumer's current level of knowledge and understanding about the use of ICT in healthcare, we asked the respondents whether they had any idea that, ICT (mobile phone, laptop computer, internet or social networks) could be used in obtaining healthcare services. Our survey revealed that, 40% of the respondents (237 out of 592) have knowledge and idea about existing m/e-Health systems regardless of their personal experience of applying or using those systems.

2.3.3 Perception of Possible Uses of ICT in Healthcare

To know the consumer's perception of the possible uses of ICT in healthcare, we asked the respondents to name the best possible use of ICT in obtaining healthcare services.

Table 2.2 Consumers' perception of possible uses of ICT in healthcare

Possible use of ICT in healthcare [n = 592]		
Possible Use	Frequency	Percentage
Setting appointment with doctors	320	54.0%
Knowing availability of doctors	145	24.5%
No comment	44	7.5%
Direct consultation	35	6.0%
Requesting home visit	27	4.5%
Prescription clarification	21	3.5%

Table 2.2 shows, 54% of the respondents think 'setting an appointment with doctors' could be the best possible use of ICT in healthcare while 'knowing the availability of doctors' is the second best possible use according to around 25% respondents. This finding clearly depicts that, a large number of our rural consumers are still ignorant about the recent uses of ICT in healthcare including remote consultation with doctors, getting virtual prescriptions and emergency medical alert systems etc.

2.3.4 Knowledge and Experience with PHC

At this point, we wanted to explore the respondents' knowledge about and experience of PHC and the findings are shown in Figure 2.1.

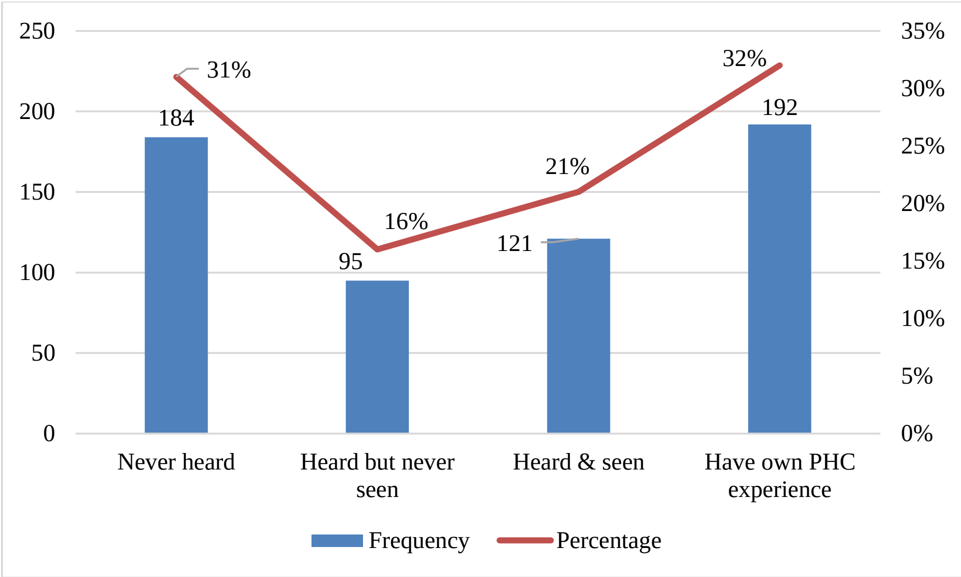


Figure 2.1 Knowledge and experience with PHC (n = 592)

The figure shows 31% of our total respondents do not know anything about PHC, whereas 16% knows about it but never seen it in person, 20% knows about PHC and have also seen it and 32% of our total respondents have own experience with PHC i.e. have received healthcare services from PHC at least once. Our finding shows, although 40% of our total respondents were somehow aware of eHealth but when the question was about their personal experience, the rate dropped down from 40% to 32%.

2.3.5 Reasons for Using PHC

We wanted to explore the major reasons for using PHC from the current PHC users (n = 192) as well as the reasons for not using PHC from the non-users (n = 400).

Table 2.3 Reasons for using healthcare services from PHC

Reasons for using PHC [n = 192]	
Less costly than conventional	30.3%
Time-saving	29.7%

Consulting with a specialist doctor	18.8%
Easy access	17.0%
Try something new	1.9%
Reference from others	1.4%
Influenced by a promotional campaign	0.9%

Table 2.3 shows, 30.3% consumers used PHC because of its less priced healthcare services in comparison with traditional healthcare service providers. Other major reasons for using PHC are less time consuming, the opportunity of virtual consultation with specialist doctors located in PHC call center, easy access etc.

2.3.6 Reasons for Not Using PHC

Table 2.4 Reasons for not using healthcare services from PHC

Reasons for not using PHC [n = 400]	
Comfortable with conventional system	38.2%
I'm not sick	18.5%
Irregular presence of PHC	16.6%
Don't know about PHC	13.5%
Don't believe the system	11.3%
Not interested to try something new	1.3%
Seems more costly	0.6%

Table 2.4 shows, 38.2% of the respondents said that they were quite comfortable with their current healthcare service providers and thus were not interested to switch to a new

system. Other major reasons are the irregular presence of PHC, lack of information about PHC among its target consumers and lack of system trust.

2.4 Implications

In this section, we are going to see how the research findings will help PHC to modify or redefine its service offerings and make it more sustainable and reachable to all segments of the society.

2.4.1 In Achieving Cost Effectiveness

Figure 2.2 shows, there is a positive (R^2 = 63%) relationship between patient's age and PHC use. It means, as age goes up the tendency to receive healthcare services also goes up. However, our finding shows that the largest consumer group of PHC is from the age group between 46 and 60.

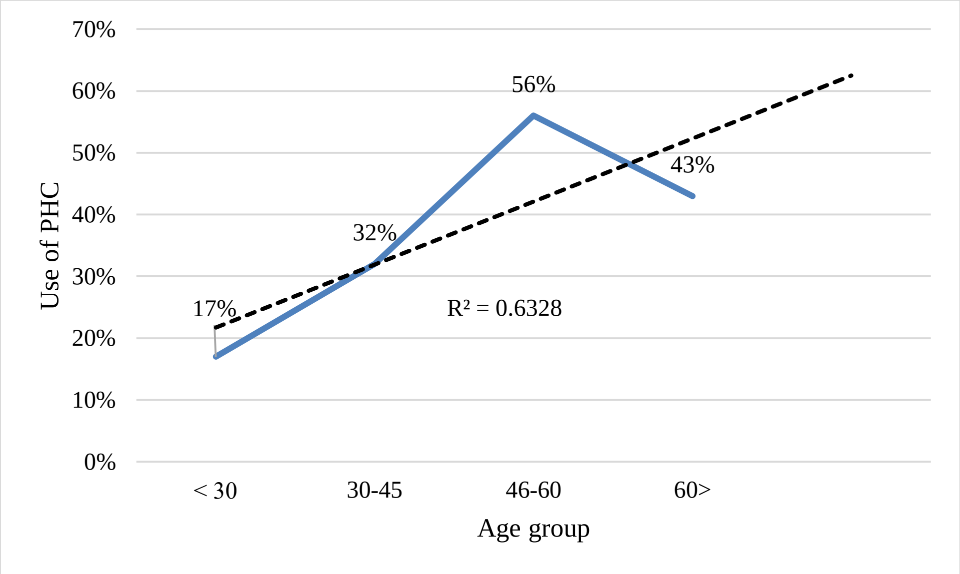


Figure 2.2 Relationship between age and PHC acceptance

After knowing the major consumer segments of PHC by age group, we wanted to their most demanding healthcare services by analyzing the central database, and the results are shown in Table 2.5.

Table 2.5 Most demanding healthcare services of PHC

	Number	Percentage
Total Patients Served (until August 31, 2016)	35,482	100.0%
Age (46-60) Patients	14,065	39.6%
Most Demanding PHC Services		
Blood Glucose (Diabetes)	13,196	94%
Blood Pressure (Hypertension)	13,080	93%
Height-Weight: BMI	9,869	70%

This finding says, not all the healthcare services provided by PHC are equally demanded by its patients. Currently, PHC offers 15+ different checkups or measurements, among which the following checkups have very few or no demand: blood cholesterol, blood haemoglobin, urine glucose, urine protein, uric acid test etc. However, currently, in each PHC box, it has to maintain all the equipment and sensors having both high, low or no demand. In order to ensure more cost-effectiveness, PHC should decrease or eliminate those medical equipment having less or no use. Or it can share those medical equipments and sensors among different boxes serving in the proximate areas.

2.4.2 In Price Adjustment

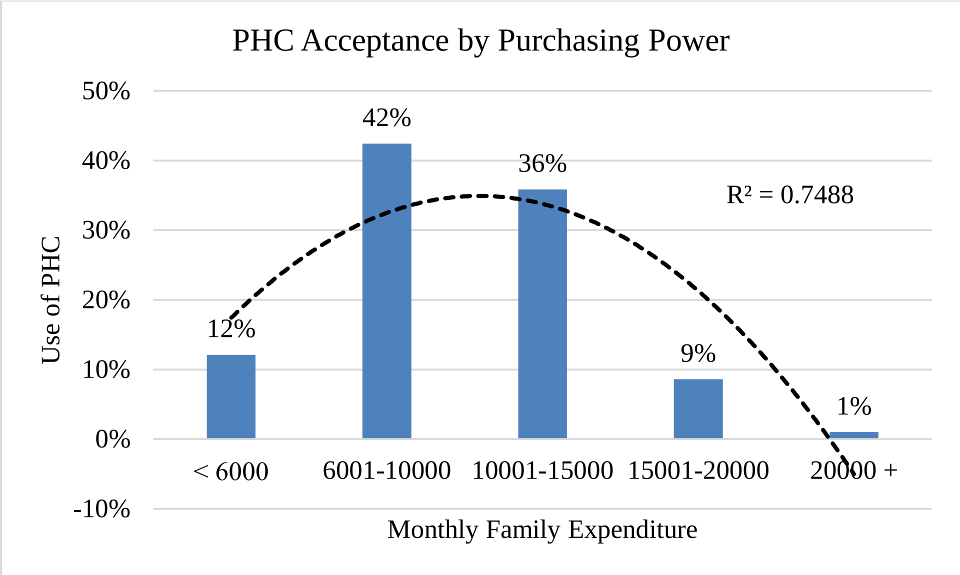


Figure 2.3 Relationship between purchasing power and use of PHC

The relationship between use of PHC and its consumers' purchasing power depicted in Figure 2.3 shows that, PHC is mostly serving the rural middle income and lower middle-income group who spend between BDT 6,000 to 15,000 a month i.e., between UDD 2.5 to USD 4.0 per day for rural lower middle-income group and between USD 4.0 to USD 6.0 for rural middle-income group. People from the lowest rural income group who spend less than BDT 6,000 per month i.e., less than USD 2.5 a day are still under-served. Since the ultimate goal of PHC is to provide affordable quality healthcare services to the under-served people, PHC should reduce its service price to make it more affordable. However, how much price adjustment will be needed to cover the bottom of the pyramid will be another research issue.

2.4.3 In Redefining Service Strategies

Since consumer behavior has an ever-changing phenomenon, consumers' needs, requirements, perceptions and priorities change frequently. This is why service providers should also change their service dimensions and strategies to adapt with the changing environment.

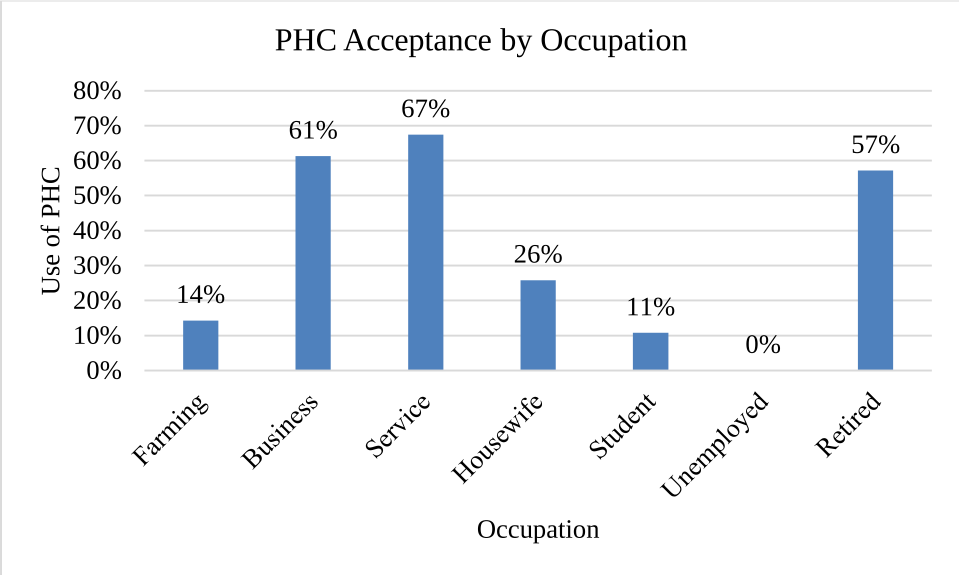


Figure 2.4 Relationship between occupation and use of PHC

Table 2.6 Distribution of PHC users by occupation

	Observed Occupation (N=573)							
	Farming	Business	Service	Housewife	Student	Unemployed	Retired	Total
PHC user	11	57	60	47	13	0	4	192
Non-user	66	36	29	135	108	4	3	381
Total	77	93	89	182	121	4	7	**573**

The above finding shows, farmer and housewife are the least served occupation by PHC. So, in order to ensure more social inclusion, PHC should take some more effective marketing strategies to promote itself, especially among farmers and housewives. In order to attract more female patients, PHC should its privacy. And in order to attract more farmers, PHC should change or its service delivery time. Because when PHC provides its healthcare services, farmers usually work in their farming lands at the same time.

2.5 Conclusion

Since the long-term sustainability of any eHealth initiative largely depends on its consumer's acceptance, this is high time to explore their behavior. In this research, we found that, a significant portion (40%) of our rural consumer of healthcare were aware of eHealth, while 32% of our total respondents accepted PHC for at least once. The finding clearly depicts that, a large number of our rural consumers are still ignorant about the recent uses of ICT in healthcare including remote consultation with doctors, getting virtual prescriptions and emergency medical alert systems etc. The major reasons for consumer's acceptance of PHC include less costly, less time consuming, the opportunity for virtual consultation with specialist doctors and easy access. While the major reasons for not accepting PHC are lack of consumer's readiness to switch from conventional healthcare platform to e-Health, lack of knowledge on eHealth and irregular presence of PHC in its service area. The findings will help eHealth service providers to design and develop their services in accordance with the perceptions and expectations of their target consumers. This will also enhance the possibility of wide-spread social adoption and sustainable operation of eHealth services among rural communities in developing countries.

Chapter 3: Acceptance Behavior

3.1 Introduction

The second step of understanding the overall consumer behavior of a technology-based service is to understand the factors or forces behind the acceptance of that new technology by its target users [27], [57]. There are several categories of factors that affect consumer acceptance of a new technology such as demographic factors (age, gender, location); socioeconomic factors (income, education, employment status etc.); behavioral factors (perception and attitude towards the technology); technical factors (ease of technology, compatibility, service quality, service delivery time etc.); promotional factors (advertisements, social reference) and other facilitators. However, not all these factors affect consumers' acceptance behavior equally rather intensity varies based on the type of service and technology used and of course, based on the type of consumers it serves. In this chapter, we are going to explore and evaluate the factors affecting consumer acceptance of eHealth with their relative intensities based on Technology Acceptance Model (TAM) and its related models. Finally, we are going to propose a dedicated 'eHealth Acceptance Model' for the rural consumers in developing countries like Bangladesh.

Healthcare, being one of the basic human needs, has become a universal demand. However, due to the lack of necessary infrastructure, insufficient qualified healthcare workforce and expensive access to quality healthcare rural inhabitants especially in developing and under-developed countries are deprived of quality healthcare services. In this circumstance, the concept of eHealth has been emerged and gained a good momentum. eHealth is an umbrella that includes a spectrum of technologies including computers, telephony and wireless communications to provide access to health care providers, care management and education [10]. Globally, eHealth is steadily becoming a popular platform for healthcare delivery and Bangladesh is no exception. A number of initiatives have already been implemented since the late 90's. These have mainly focused on mobile phones, especially important amongst the rural and underserved communities for their potential to overcome geographical boundaries. In 2011, WHO reported Bangladesh as one of the 15 countries using eHealth to raise health awareness [58].

PHC has started its experimental service since 2010. Until January 31, 2018, it reached 32 remote locations in 9 districts and served 41,240 rural patients among which 55.2% were male and 44.8% female [39]. For our research, we selected Bheramara sub-district of Kushtia as our data collection site which is one of the above mentioned 9 Districts, located in the North-Western part of Bangladesh. PHC started serving in Bheramara from 2012 and served 4701 rural patients until the above-mentioned date.

3.2 Background and Objective

Research related to eHealth and health IT often focuses more on IT design and implementation [18], and probably not enough on how the end users react towards already implemented IT [59]. The success of health IT doesn't only depend on its design and infrastructure but also on its end-users' acceptance for whom the service is being designed [24]. However, some recent studies explored that in spite of assuming potential benefits, the adoption rate of eHealth is insignificant in Bangladesh, especially among rural inhabitants. Ahmed et al. [20] found, people were somehow aware of eHealth and considered it as a potentially useful service, however, a very few had actually used them. Khan et al. [21] found expensive consultation fees, lack of technical knowledge to operate the system and lack of trust in unknown physicians are the leading obstacles to adopt eHealth in Bangladesh. Hoque et al. [22] investigated the influence of cultural dimensions on the adoption of eHealth in urban society in Bangladesh. Khatun et al. [23] found Illiteracy, lack of English language proficiency, lack of trust and technological incapability are pulling behind rural Bangladeshi communities to adopt e/mHealth, whereas a sense of ownership, evidence of utility, a positive attitude, and intention of future were driving forces in the adoption process. Hoque and Sorwar [60] investigated the underlying factors influencing the adoption of mHealth by urban elderly in Bangladesh. Hossain et al. [6] investigated demographic and socio-economic factors that affect rural inhabitants' acceptance of eHealth in Bangladesh.

Above literature review depicts, most of the existing studies are focused on IT design and implementation, system architecture and infrastructural issues of eHealth. Some described the importance eHealth in public health development including its ancillaries and barriers to mass adoption [20]–[23]. Some studies separately measured the impact of cultural factors [22], demography and socio-economic factors [6] on eHealth adoption. However, not enough studies are conducted to explore the rural end-users' acceptance of eHealth, especially from the perspective of developing nations. It is, therefore, become necessary to measure the combined impact of demographic, behavioral, technical and promotional factors on end-users' acceptance of eHealth. The objective of this study is to explore the factors that affect rural end-users' acceptance of eHealth in a developing country like Bangladesh.

3.3 Research Framework and Hypothesis

In last three decades, several theories have been developed to explain the factors affecting individuals' acceptance new technologies or technology-based services. The most renowned and frequently used theories are Technology Acceptance Model (TAM), TAM 2, Theory of Planned Behavior (TPB), Theory of Reasoned Action (TRA), Combined TAM and TPB and the Unified Theory of Acceptance and Use of Technology (UTAUT). Technology Acceptance Model (TAM) first was established by Fred Davis in 1989 as a theory of information system that models how users understand, approach, utilize, come to accept and use a technology [61]. TAM2 added cognitive and social influences to predict technology acceptance. The cognitive aspect included perceived ease of use, job relevance, quality of output and results demonstrability. While social influences focused mainly on subjective norms and voluntariness [62]. The Theory of Planned Behavior (TPB) originally evolved from the TRA with an added variable perceived behavior control [63]. The UTAUT model derived by comprehensive examination of various models mentioned above aiming to achieve a unified view of user acceptance [64].

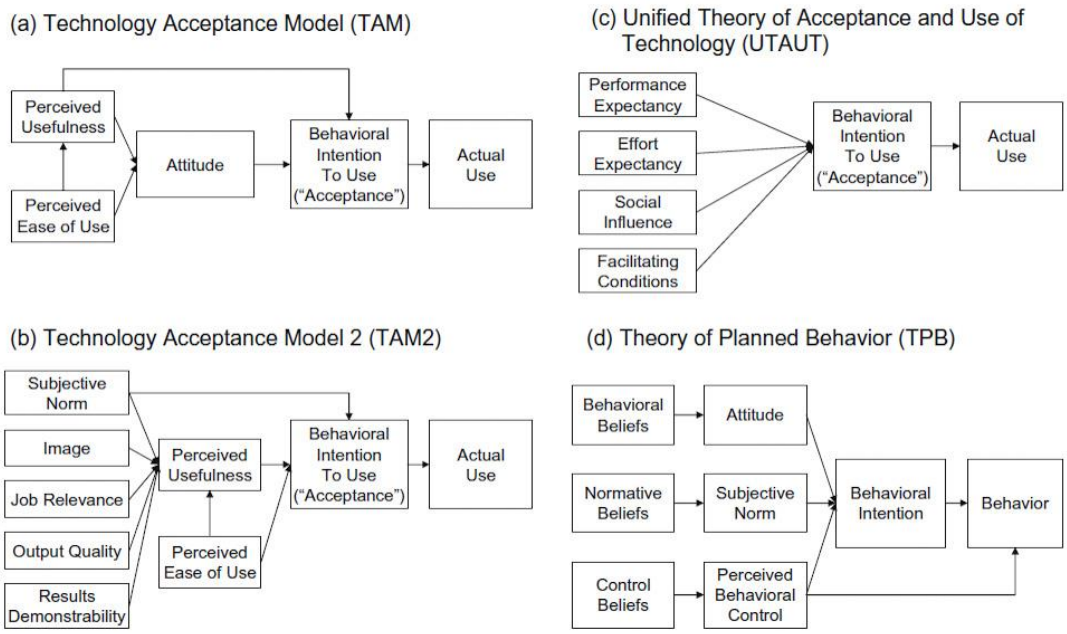


Figure 3.1 TAM related models

To attain the research objective, this study adopts Technology Acceptance Model (TAM) which is the most notable model to explain end-users' behavior in health IT [65]. Although TAM is widely used in healthcare research, it should be kept in mind that, this model is not developed solely for healthcare. Researchers have applied this model in e-commerce [66]; e-banking [67]; online ticketing system [68]; office productivity software [69]; social media [70]; virtual archive [71] and in many other IT product or services. Thus Holden et al. [59] suggested, if TAM is used in its generic form, it may not capture some of the unique contextual features of IT-based healthcare delivery systems. This is why we proposed an extended eHealth acceptance model based on TAM and its related models which is shown in Figure 3.2 as our research framework.

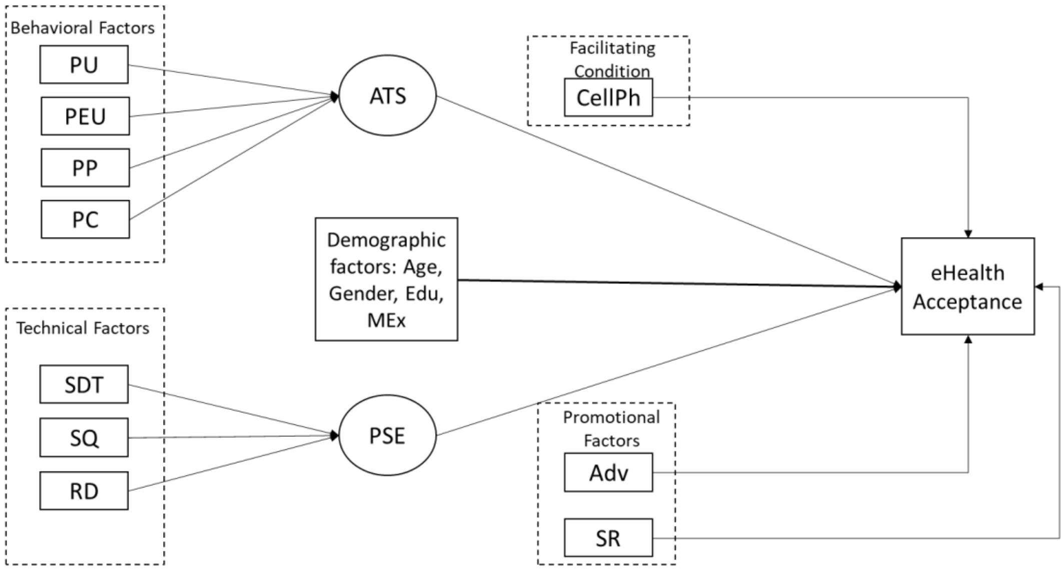


Figure 3.2 Proposed eHealth acceptance model

Note: PU = perceived usefulness; PEU = perceived ease of use; PP = perceived privacy; PC = perceived cost; ATS = attitude towards the system; SDT = service delivery time; SQ = service quality; RD = result demonstrability; PSE = perceived system effectiveness; MEx = monthly family expenditure; Adv = advertisements; SR = social reference

In this proposed framework, perceived usefulness (PU); perceived ease of use (PEU) and attitude towards the system (ATS) were adopted from the original TAM proposed by Davis [61]. Service quality (SQ) and result demonstrability (RD) were adopted from TAM2 [62]. Social reference (SR) and facilitating condition were adopted from UTAUT [64]. The model also incorporates a few additional variables based on existing literature and empirical evidences in order to have a better understanding of consumers' acceptance behavior towards eHealth, which are perceived cost [72], perceived privacy [73], service delivery time [74], perceived system effectiveness [75], and impact of advertisement [76].

Demography

Several studies [77]–[79] confirmed the profound impact of demographic factors such as age, gender, income, education etc. on consumers' buying behavior and decision-making process. Thus we also wanted to explore the impact of demography on rural end-users' acceptance of eHealth.

H1. Age has a positive impact on end-users' acceptance of eHealth

H2. Gender has an impact on end-users' acceptance of eHealth

H3. Level of education has a positive impact on end-users' acceptance of eHealth

H4. Monthly family expenditure has a positive impact on end-users' acceptance of eHealth

Attitude

Davis [61] defined attitude as individual's evaluative judgment of the target behavior on some dimension (e.g., good/bad, harmful/beneficial, pleasant/unpleasant). Aizen et al. [80] defined attitude as the degree to which a person likes or dislikes any object. In our study, we considered attitude as a latent variable which has been extracted from four other observed variables namely perceived usefulness, perceived ease of use, perceived privacy, and perceived cost.

H5. Attitude towards eHealth has a favourable impact on end-users' acceptance of eHealth

Perceived system effectiveness

System effectiveness has been defined as the extent to which a system can be expected to achieve its goals within its specific environment. The effectiveness of the system depends on its output quality, visibility, timeliness, and reliability [75], [81]. In our study, we considered perceived system effectiveness as a latent variable which has been extracted from three more observed variables namely service delivery time, service quality, and result demonstrability.

H6. Perceived system effectiveness has a positive influence on end-users' acceptance of eHealth

Facilitating condition

Refers to the factors that facilitate or encourage a particular behavior to occur in a given environment. It also includes an existing technical infrastructure to support using any new system [64]. In our study, we considered cellphone ownership as a facilitator of using eHealth.

H7. Cellphone ownership positively influence the acceptance of eHealth

Promotion

Promotion, in marketing, is any type of communication aimed to inform the relative merits of a product or service to its target audiences and encourage them to use it. The goal of promotion is to increase awareness, create interest, and finally generate sales [82]. Promotion plays a vital role in healthcare initiatives to be accepted by its target consumers [76]. Since PHC does periodic promotional campaigns in its service area, we are interested to see its impact on consumers' response.

H8. Exposed to advertisement has a positive impact on end-users' acceptance of eHealth

Social reference

People become influenced when someone considered to be important to them refer any particular product or service or encourage to exhibit a given behavior [62], [64]. The referee can be anyone from friends and family, coworkers or acquaintance.

H9. Social reference has a positive impact on end-users' acceptance of eHealth

In this study, we consider end-users' acceptance as the response of actual users who received any healthcare service from Portable Health Clinic (PHC) system at least once.

3.4 Methods

The study is exploratory [50] and quantitative in nature. Data were collected between June and July 2016 through a field survey conducted in Bheramara sub-district of Kushtia, a North-Western district of Bangladesh. A structured questionnaire was developed initially in English, which later on, was translated into Bengali (the local language of Bangladesh). Close-ended questions were used to extract respondents' demography and a five-point Likert-scale from extremely disagree to extremely agree with a neutral point on 3 was used to extract the cognitive information. A pilot study was conducted 7 randomly selected 18+ rural inhabitants to test the understandability of the questionnaire. Their feedback was considered to review the questionnaire. To maintain the right of privacy of the respondents, they have been briefed on the research purpose and asked whether they want to participate in the survey as well allow us to use their response in our scientific publications.

A total of 592 questionnaire was distributed randomly, however, after deducting missing fields and partially answered questionnaires we could include 292 respondents as our effective sample. The sample was drawn by a simple random sampling method which eliminates the bias by giving all individuals an equal chance to be chosen [51]. There is a variety of opinions regarding the optimum sample size for different types of statistical analysis. According to Bartlett et al. [52], a sample of 200 as fair and 300 as good for statistical analysis including logistic regression modeling. Malhotra [53] suggested 200 as a critical sample size that can be used in any common estimation procedure for valid results. Kenny [54] suggested, in behavioral science with multivariate analysis the sample size should be at least 10 times the number of items in the study. In our study, the model consists of 15 items including both independent and dependent. As per above studies, we considered a sample size of 292 is optimum for our study.

Lee et al. [83] conducted a meta-analysis on 101 TAM oriented articles published in leading IS journals and conferences from 1986 to June 2003 and found 87% research conducted the non-longitudinal study, 85% collected data through field survey, and 32% research used regression modeling as their analysis method. Our proposed model is constructed with logistic regression. Data was collected through field survey with a structured questionnaire and analyzed with logistic regression and other statistical tools including principal component analysis, factor analysis, reliability test, Pearson correlation test etc.

3.5 Results

3.5.1 Respondents' demography

Respondents' demographic characteristics are shown in Table 3.1.

Table 3.1 Respondents' demography (n = 292)

	Frequency	Percentage
Gender		
Male	205	70.0%
Female	87	30.0%
Age group		
<30	67	22.9%
30-45	148	50.6%
46-60	64	21.9%
60>	13	4.5%
Education		
None	23	8.0%
Primary	72	25.0%
Secondary	114	39.0%
College & Higher	83	28.0%
Monthly family expenditure (in BDT)		
Less than 6,000	31	11.0%
6,001 – 10,000	118	40.0%
10,001 – 15,000	100	34.0%
15,001 – 20,000	30	10.0%
More than 20,000	13	4.0%
Cellphone ownership		
Yes	252	86.0%
No	40	14.0%
eHealth (PHC) use		
Yes	171	58.0%
No	121	42.0%

3.5.2 Descriptive statistics of observed variables

As mentioned earlier, a five-point Likert scale was used to measure the cognitive aspects of the respondents i.e. their perception and attitude towards eHealth. To do so, seven observed variables have been measured and the descriptive statistics are shown below:

Table 3.2 Descriptive statistics of observed variables

	PU	PEU	PP	PC	SDT	SQ	RD
Mean	3.52	3.29	3.18	3.82	3.68	3.32	3.26
Standard Deviation	0.91	0.70	0.66	1.10	0.83	0.75	0.68
Count	292	292	292	292	292	292	292

These statistics show, perceived cost and service delivery time received the most favorable response while privacy and result demonstrability remained less favorable. In other words, respondents considered PHC service cost as cheaper and delivery time as faster than that of other existing traditional healthcare services. On the other hand, people are concerned about their privacy and result understandability while using eHealth.

3.5.3 Extraction of latent variables

Two latent variables (ATS & PSE) have been extracted from seven observed variables (PU, PEU, PP, PC, STD, SQ & RD) by applying maximum likelihood factor analysis with varimax rotation [84]. Then, internal consistency among variables has been measured with item analysis, commonly known as reliability test keeping Cronbach's alpha value as the prime consideration [85].

Table 3.3 Results of factor analysis and reliability test

Variable	Factor1 (ATS) Loading	Factor2 (PSE) Loading	Cronbach's alpha
PU	0.646	0.241	
PEU	0.737	0.122	
PP	0.697	0.121	0.7803
PC	0.647	0.249	

SDT	0.181	0.745	
SQ	0.203	0.797	0.7997
RD	0.173	0.668	

The higher positive loadings for PU, PEU, PP, and PC indicate their strong influence on ATS. Similarly, PSE can be explained well with SDT, SQ, and RD. In both cases, the Cronbach's alpha value is higher than the standard threshold of 0.70 which indicates the constructs of latent variables are internally consistent enough [85].

3.5.4 Correlation among independent variables

A Pearson correlation matrix was prepared to test whether any multicollinearity exists among independent variables before moving them into the final model.

Table 3.4 Correlation matrix of independent variables

	Age	Gender	Edu	MEx	ATS	PSE	CellPh	Adv	SR
Age	1.00								
Gender	0.33	1.00							
Edu	-0.31	0.02	1.00						
MEx	0.21	0.16	0.32	1.00					
ATS	0.22	0.01	-0.11	-0.06	1.00				
PSE	0.15	0.14	-0.06	-0.04	0.11	1.00			
CellPh	-0.24	0.05	0.17	0.09	-0.01	0.03	1.00		
Adv	0.14	0.05	-0.03	-0.03	0.16	0.20	-0.03	1.00	
SR	0.09	0.12	-0.01	0.01	0.25	0.14	-0.08	-0.02	1.00

The matrix shows no multicollinearity exists among independent variables since all the correlation coefficients are less than 0.40 which was referred as a threshold value by many researchers [86].

3.5.5 Results of hypothesis testing

A logistic regression modeling is used to test the hypothesis. A significance level of 0.05 is considered for this model. Decisions regarding hypothesis testing have been taken by comparing the variables' P-value with models' significance level. Regression coefficient indicates the nature of the relationship between independent and dependent variable while odds ratio explains the effect of independent variables on the dependent variable.

Table 3.5 Results of regression analysis

H.	Variable	Coef.	OR	95% CI	P-value	Result
1.	Age	0.062	1.0641	(1.0212, 1.1088)	0.002	Supported
2.	Gender				0.033	Supported
	-Female	Ref.	Ref.	Ref.		
	-Male	1.003	2.7271	(1.0658, 6.9776)		
3.	Education				0.032	Supported
	-None	Ref.	Ref.	Ref.		
	-Primary	2.028	7.5995	(1.5170, 38.0706)		
	-Secondary	0.925	2.5229	(0.5501, 11.5717)		
	-College & Higher	0.638	1.8926	(0.3588, 9.9814)		
4.	MEx				0.247	Not Supported
	<6000	Ref.	Ref.	Ref.		
	6001-10000	-0.330	0.7191	(0.1991, 2.5968)		
	10001-15000	0.434	1.5436	(0.4049, 5.8842)		
	15001-20000	-0.409	0.6644	(0.1160, 3.8064)		
	20000>	-1.50	0.2229	(0.0211, 2.3516)		
5.	ATS	1.518	4.5609	(2.7149, 7.6620)	0.000	Supported
6.	PSE	0.744	2.1046	(1.3907, 3.1849)	0.000	Supported
7.	CellPh	1.366	3.9181	(1.2850, 11.9473)	0.014	Supported
8.	Adv	1.937	6.9394	(2.7725, 17.3688)	0.000	Supported
9.	SR	2.275	9.7297	(4.1551, 22.7834)	0.000	Supported

Note: Ref. = Reference Level; OR = Odds Ratio; CI = Confidence Interval

The finding says, among demographic factors age, gender, and education have significant impact on rural end-users' acceptance of eHealth while we didn't find any significant influence of monthly family expenditure of the respondents on their eHealth acceptance behavior. People having a positive attitude towards eHealth are 4.56 times more likely to use it than those having a negative attitude. People who believe the system is effective are 2.10 times more likely to use eHealth than those who don’t believe. Those who have access to cellphone are 3.92 times more likely to use eHealth than those who don’t have. People who have exposed to advertisements or promotional campaigns are 6.94 times more likely to use eHealth than those who don’t have. People who have social reference are 9.73 times more likely to use eHealth than those who don’t have any reference.

3.5.6 Model summary and goodness-of-fit

Our model has a deviance R^2 of 54.70 which means the model explains 54.70% of the deviance in the response variable. For binary logistic regression, the ‘Hosmer-Lemeshow’ test is a more trustworthy indicator of how well the model fits the data [87]. In this model, the goodness-of-fit score is 0.539 which is greater than the significance level of 0.05, which indicates that there is not enough evidence to conclude that the model does not fit the data.

3.6 Comparison of Model Performance

Five contemporary research models related to remote healthcare systems based on TAM and its related models have been selected out of 33 research articles published between the year of 2000 and 2018 in either ISI or JCR indexed peer-reviewed journals to be evaluated and compared their performance with our proposed model. The model selection process is shown in Figure 3.3.

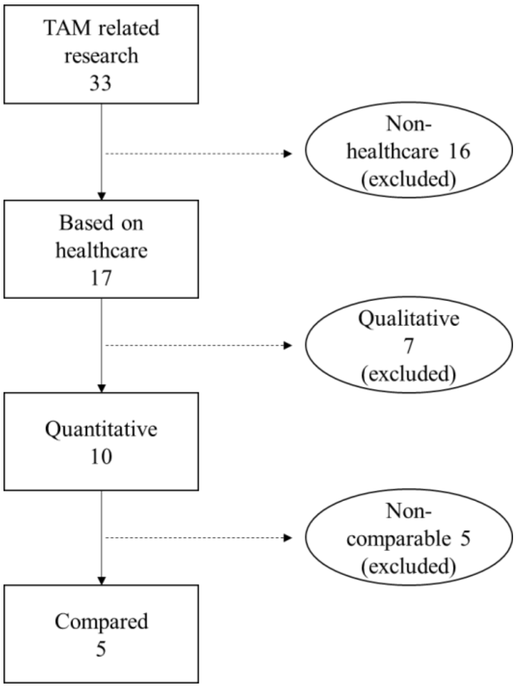


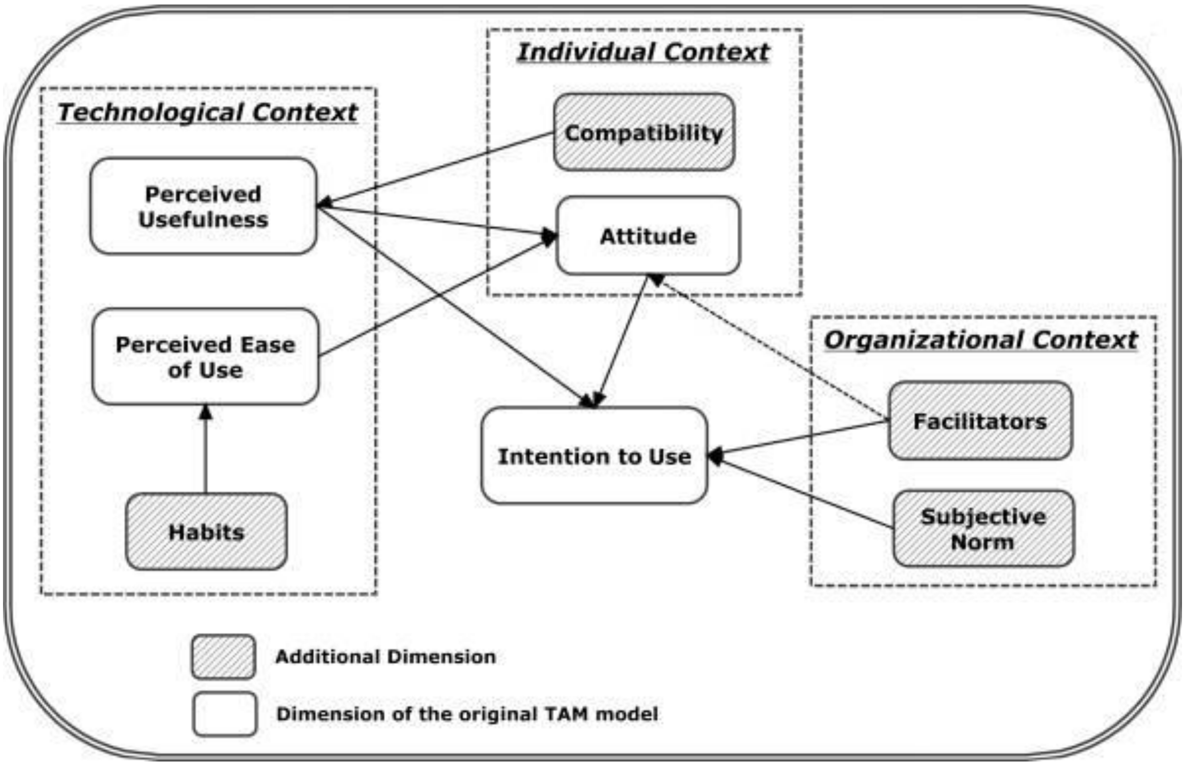
Figure 3.3 Model selection process for comparison

The performance of any specific model is measured by the coefficient of determination, commonly known as R^2 which explains the variance of dependent variable due to the changes in the models' set of independent variables. However, it is literally impossible to have the exact same number of sample size and independent variables for all the models. Therefore, researchers compare models with a dissimilar number of sample and independent variable through adjusted R^2 where the value of R^2 is adjusted with the sample size and number of independent variables in the model [88], [89].

The performance comparison among five models including our proposed model are shown in the following section starting from next page.

Model: 1

Objective: To Evaluate Healthcare Professionals' Adoption of a New Telemonitoring System



Sample size (n) = 93 (72 nurses & 21 doctors from Basque Country, Spain)

Number of independent variables = 7

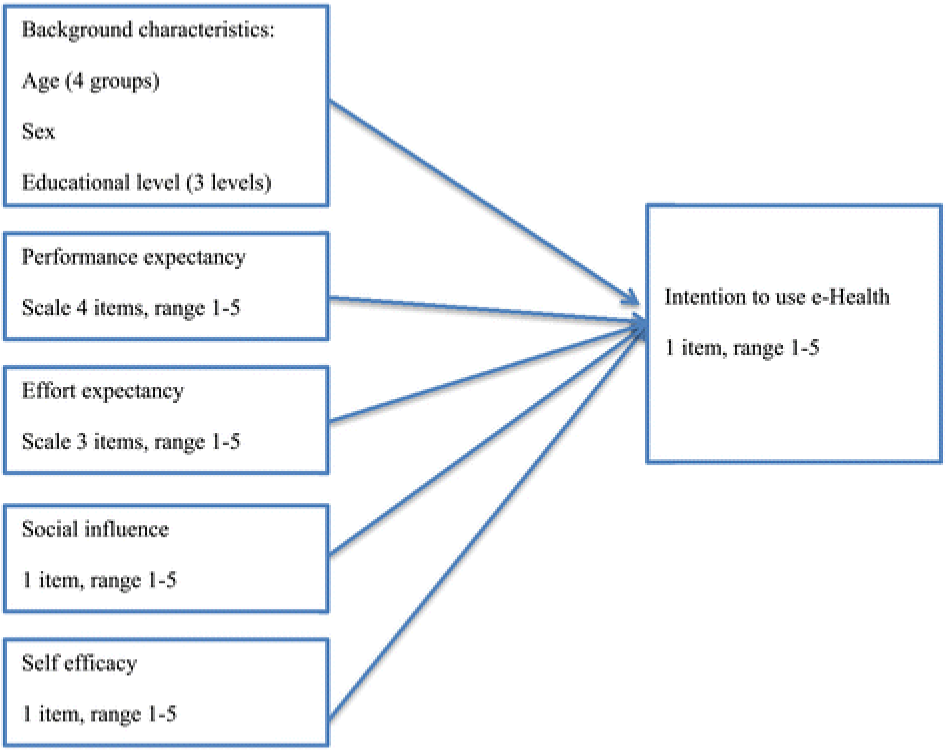
Method: Logistic regression

Coefficient of determination (R^2) = 0.42

Adjusted R^2 = 0.37

Model: 2

Objective: To measure the intention of using eHealth by senior citizens



Sample size (n) = 1014 Dutch (age between 57 and 77)

Number of independent variables = 7

Method: Multiple Linear Regression

Coefficient of determination (R^2) = 0.41

Adjusted R^2 = 0.40

Model: 3

Objective: To understand the factors affecting mHealth adoption by the elderly

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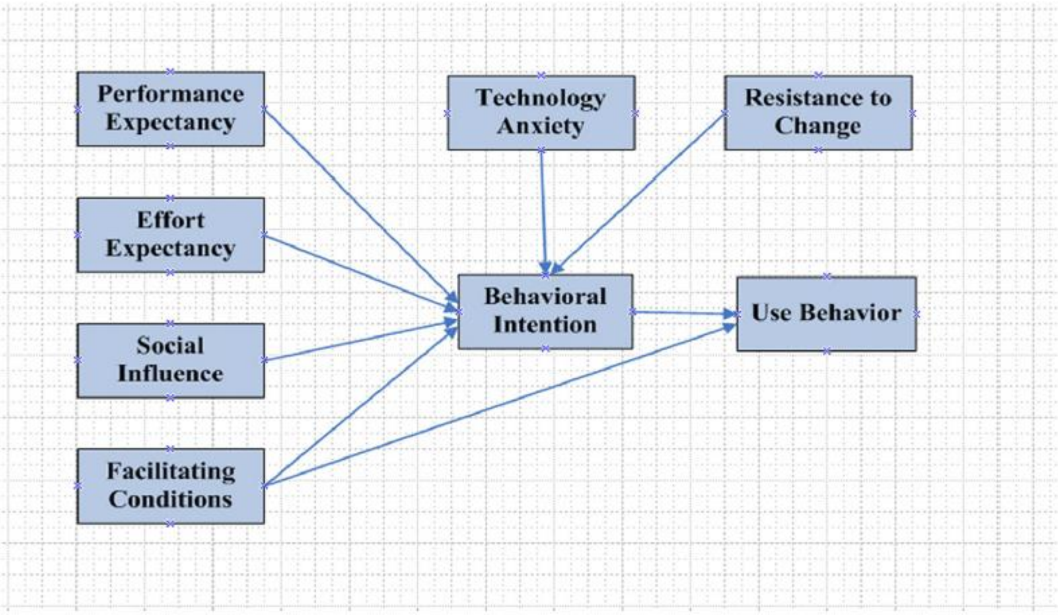


Fig. 1. Research Model.

Sample size (n) = 277 (age 60+ from Dhaka city, Bangladesh)

Number of independent variables = 7

Method: Partial Least Square (PLS) modeling

Coefficient of determination (R^2) = 0.39

Adjusted R^2 = 0.37

Model: 4

Objective: To explore the causes of eHealth acceptance in urban Iran

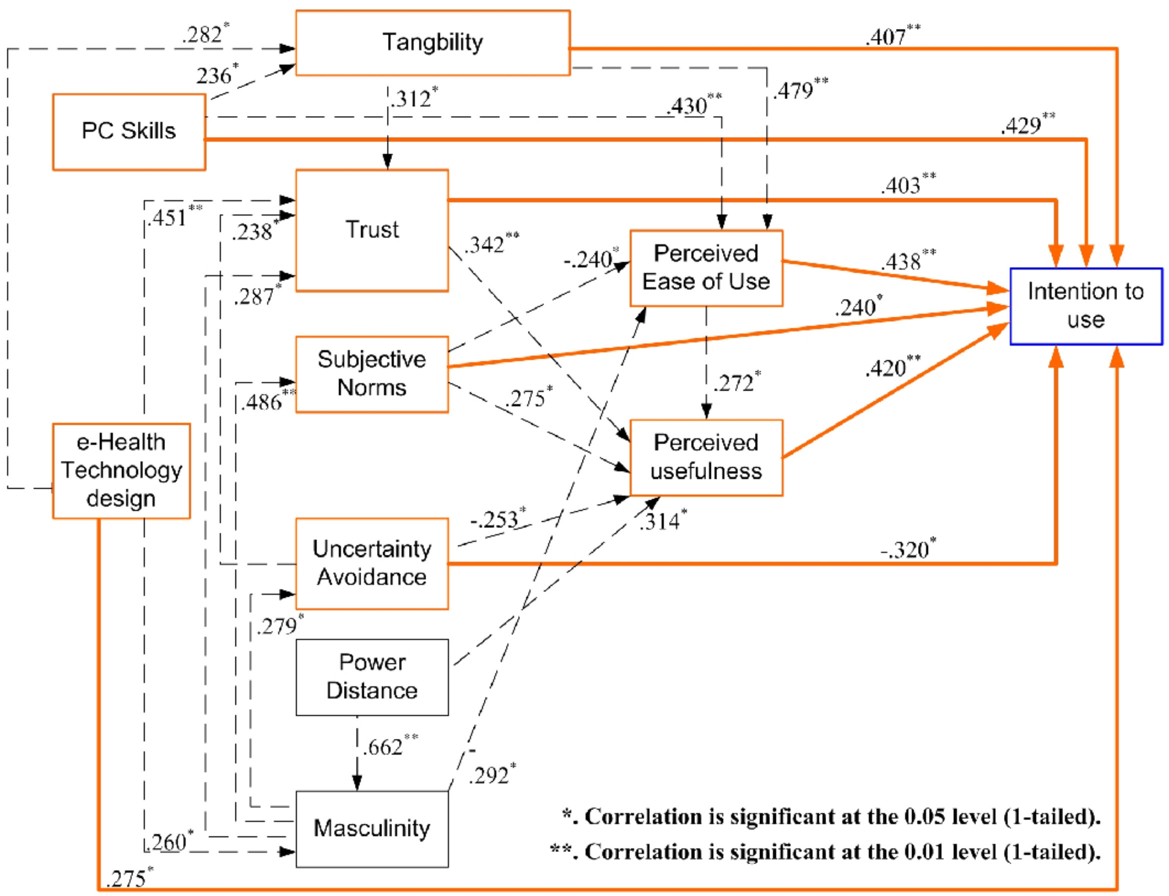


Figure 2: e-HTAM constructs correlation association diagram

Sample size (n) = 358

Number of independent variables = 10

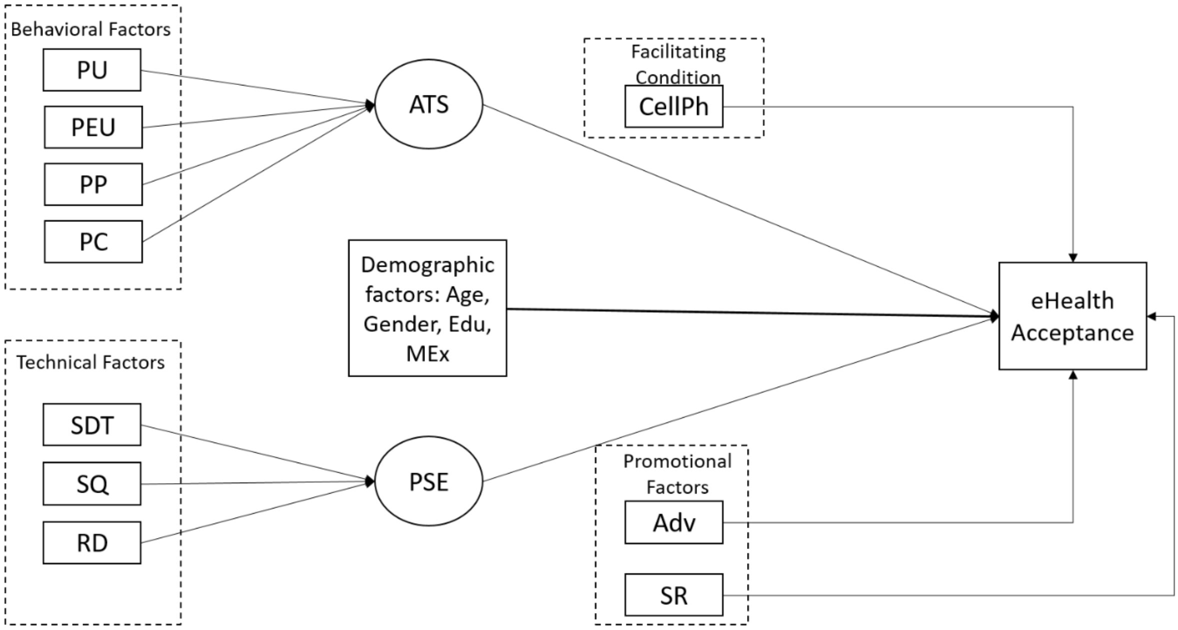
Method = Structural Equation Modeling (SEM)

Coefficient of determination (R^2) = 0.52

Adjusted R^2 = 0.49

Model: 5 (Our approach)

Objective: To identify the factors influencing rural end-users' acceptance of eHealth



Sample size (n) = 292

Number of independent variables = 14

Method = Logistic regression modeling

Coefficient of determination (R^2) = 0.54

Adjusted R^2 = 0.51

The summary of the findings is shown in the following Table 3.6.

Table 3.6 Summary of model comparison

Authors	**Objective**	**Study Area**	**Method**	**N**	**Independent variables**						**R^2**	**R^2 (Adj)**
					Total	Demo	TAM	UTAUT	TPB	Contributed		
Gagnon et al. 2012 [90]	To evaluate the healthcare professionals' adoption of telemonitoring systems	Basque, Spain	Logistic Regression Modeling	93 (72 nurses + 21 doctors)	7	0	3	1	1	2 • Compatibility • Habit	0.42	0.37
Veer et al. 2015 [91]	To measure the intention of using eHealth by senior citizens	Tilburg, Netherlands	Multiple Linear Regression	1014 (age 57-77)	7	3	0	3	0	1 • Self-efficacy	0.41	0.40
Hoque et al. 2017 [60]	To understand the factors affecting mHealth adoption by the elderly	Dhaka, Bangladesh	Partial Least Square (PLS)	277 (age 60+)	7	0	0	5	0	2 • Technology anxiety • Resistance to change	0.39	0.37
Mohamed et al. 2011 [92]	To explore the causes eHealth acceptance in urban Iran	Tehran, Iran	Structural Equation Modeling (SEM)	358	10	0	2	3	1	4 • Trust • Tangibility • Masculinity • Power distance	0.52	0.49
Hossain et al. 2018 [93]	To identify the factors influencing rural end-users' acceptance of eHealth	Kushtia, Bangladesh	Logistic Regression Modeling	292 (age 18-76)	14	4	4	2	0	4 • Service time • Privacy • Cost • Advertisement	0.54	0.51

The finding says, our proposed model with an R^2 of 0.54 and adjusted R^2 of 0.51 performed slightly better (by 2%) than the existing contemporary research models shown above.

3.7 Discussion and Limitations

This study applied an extension of technology acceptance model to determine the rural end-users' acceptance behavior towards eHealth in Bangladesh. We provide empirical evidence for the hypotheses in our study. Most of our findings are consistent with previous studies applied TAM in remote healthcare systems, eHealth, and mHealth in specific. Hoque et al. and Davis found perceived usefulness (PU) and perceived ease of use (PEU) have significant impact in forming users' attitude (ATS) towards any given system [22], [61]. Venkatesh et al. explored significant influence of output quality (SQ), result demonstrability (RD) and social reference (SR) on technology acceptance [62], [64]. Brown et al., Kim et al., and Elbert et al. found perceived system effectiveness (PSE) has a positive impact on system adaptability [75], [81].

In our study, we found social reference has the strongest positive impact on eHealth acceptance with an odds ratio of 9.7 followed by advertisement (OR = 6.9), attitude (OR = 4.5); cellphone use (OR = 3.9), and perceived system effectiveness (OR = 2.1). Among demographic factors age, gender and education were found as significant influencers, however, we didn't find any significant impact of respondents' monthly family income on their acceptance of eHealth. Males were found more likely to accept eHealth since females in rural Bangladesh are less mobile due to social and cultural norms in a male-dominated society [94]. In terms of education, illiterate rural people were mostly found unaware of eHealth while people with an at least primary level of education have shown more interest in eHealth. On the other hand, higher educated rural people considered it as a temporary alternative to the mainstream healthcare services, thus remained less interested.

The study has a few limitations. We conducted this study on a rural population of a particular geography which is Bheramara, Kushtia, a North-Western district of

Bangladesh. Thus, the results may raise concerns about the generalization of the findings. Further research, therefore, can be carried out covering broader geography. Though we have extended the original TAM by adding PSE and Adv, few additional variables could be added such as users' trust and technology anxiety to gain more comprehensive insights of eHealth acceptance by rural end-users. We also believe, further longitudinal studies can be performed to observe the changes in relational pattern and strength of input variables with eHealth acceptance.

3.8 Conclusion

eHealth is relatively a new phenomenon to the rural communities in developing countries. The overall success of this initiative, therefore, doesn't simply depend on its IT design and implementation rather large-scale users' acceptance as well [6], [24]. This study attempts to explain the factors that influence rural end-users' acceptance of eHealth and found social reference as the most significantly influential factor followed by advertisement, users' attitude towards the system, access to a cellphone and perceived system effectiveness.

Thus, eHealth service providers who are intended to offer their services to rural areas in developing countries should focus more on generating social references or positive word-of-mouth. They also should conduct advertisement to create mass awareness and to inform the positive features and potential benefits of eHealth. In order to create a positive attitude towards ehealth easy-to-use system, shorter service delivery time, and affordable price should be taken care of.

The findings of this study provide an applied guideline to the successful adoption of eHealth among rural communities in developing countries. This also creates an opportunity for eHealth technology developers and service providers to have a better understanding of their end users which, in turn, will empower them to address the challenges in regards to the design and implementation of successful eHealth initiatives.

Chapter 4: Compliance Behavior

4.1 Introduction

Patients' non-compliance with prescription is a multifaceted healthcare problem. The reasons may be associated with the patient, treatment, and/or healthcare provider. However, as a result, patients are facing undesirable clinical outcomes and are deprived of optimal health recovery which in turns lead to increased morbidity as well as increased financial and societal costs [95]. In healthcare, the phrase 'compliance with prescription' has a broader dimension. Vrijens et al. defined compliance as the degree to which a patient is able to follow the guidelines of prescribed treatment [96]. Patients may be non-compliant in any phase of their treatment. They may decide not to collect their medicines from the pharmacy and not to start their treatment at all, which is considered as primary non-compliance. They may take more or less medication than was prescribed or use their medication at a wrong time. They may also suspend or even terminate their treatment ahead of prescribed time [97], [98]. This study, however, will focus on the factors that affect rural patients' primary non-compliance with e-prescription issued by a human-assisted remote healthcare system, namely Portable Health Clinic (PHC) in Bangladesh.

4.1.1 Trust and Compliance

Consumer trust is one of the most important issues to be understood for any technology-based service provider, especially when the service is new to the consumers. Consumer trust is an intangible concept that is not easily acquiescent to a formal black-and-white definition. However, from eHealth point of view, consumer trust means the degree to which a patient believes that the care provider is going to deliver the exact services as promised and the prescribed guidelines will be able to solve their health-related issues as expected [99], [100].

The conventional way of measuring consumer trust is conducting questionnaire survey and asking a pool of simple binary questions or five or seven-point Likert scale questions to dive into a little deep. However, in both cases, a respondent might give biased, manipulated or deliberately misleading answers which prevents a service provider to know the exact status of consumer trust [101], [102]. Keeping this scenario in mind, in this section of the study, we propose a new mechanism of measuring patients' trust towards eHealth not by asking questions but by observing their prescription compliance behavior.

4.1.2 PHC e-prescription

Handwritten prescriptions have been using as a primary means of communication between prescribers and pharmacists. Over time, the risks associated with handwritten prescriptions such as difficulties with legibility, the risk of misinterpretation etc. encouraged the adoption of electronic prescriptions [103]. E-prescribing system sends an accurate, error-free and understandable digital prescription directly to the patients or partnered pharmacies. It reduces the likelihood of adverse drug effects caused due to errors and misunderstandings in handwritten prescriptions [104]. In Bangladesh, most of the rural patients are familiar and habituated with conventional handwritten prescriptions while PHC is providing e-prescriptions issued by a remote doctor by using an electronic prescription system software. A comparison between conventional handwritten prescription and PHC's e-prescription has been shown in Table 4.1.

Table 4.1 Difference between handwritten and PHC e-prescription

Feature	Handwritten prescription	PHC e-Prescription
Electronic entry	✗	✓
Address individual patient	✓	✓
Medication monitoring	✗	✗
Access to patient's history	✗	✓
Connect to pharmacy	✗	✗
Integrate with EMR	✗	✓

Note: EMR = Electronic medical record

According to a report by the Systems for Improved Access to Pharmaceuticals and Services (SIAPS) 2015, Bangladesh has approximately 103,451 licensed retail drugstores and an estimated approximately equal number of unlicensed stores are involved in selling drugs “over-the-counter”. A majority (68%) of the clients visiting the drug shops came by self-referral and without a prescription while the rest are prescribed. Dispensing drugs on the basis of a patient’s request (83%) or a patient’s symptoms of illness (59%) is quite common [105]. However, as an experimental remote healthcare service provider, PHC has not yet incorporated partner pharmacies with its system i.e., prescriptions are not routed to the pharmacists rather a printed version is handed over to the patient. It, thus, cannot monitor patients’ medication progress.

In order to get e-prescription from PHC, a patient first, has to register his/her vital information such as name, age, sex, location and disease complaints etc. with the PHC system which generates a unique patient ID. Second, health checkup is conducted with an assistance of healthcare worker, checkup data is automatically sent and stored to the central PHC server. The next step is tele-consultancy (voice and video) between the patients in need and the remote doctor located in the headquarter of PHC. After having the conversation with patients and analyzing their clinical data, if necessary the doctor might issue an e-prescription, a printed version of that e-prescription is finally handed to the patient. The overall healthcare service delivery process of PHC is shown in Figure 4.1.

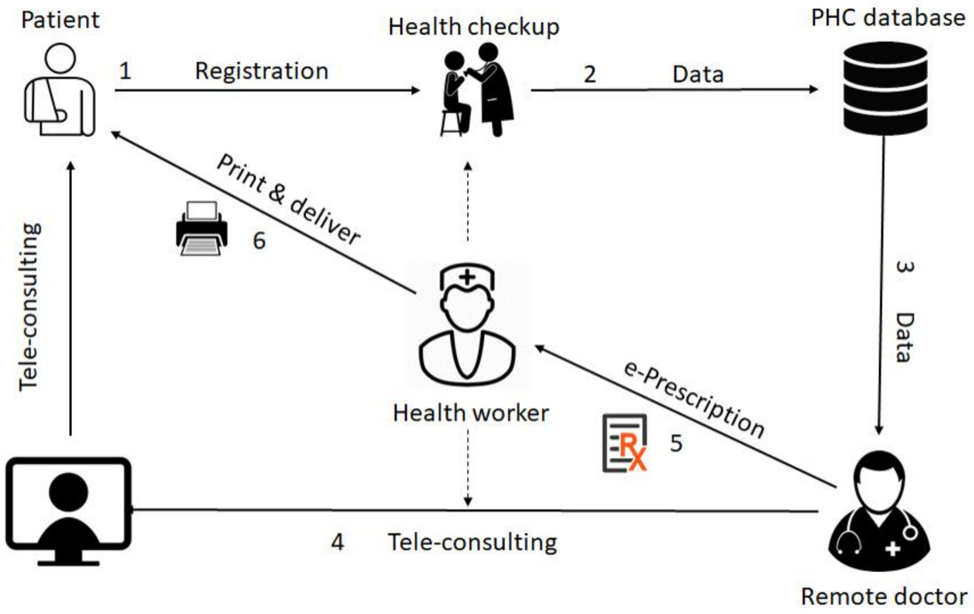


Figure 4.1 Healthcare service delivery flowchart of PHC

Portable Health Clinic is designed and targeted to provide the basic healthcare services to the under-served rural communities in Bangladesh with a view to reducing morbidity by combating against non-communicable diseases. Therefore, the majority of its patients are coming with health issues such as hypertension, anaemia, arrhythmia, lower back pain, knee joint pain, burning sensation and diabetes.

4.2 Background and Objective

The features, benefits and challenges of e-prescription system, its impact on reducing medication error and improving patient's safety and overall care quality have been widely studied. Odukoya et al [106] explained how e-prescribing can enhance the safety of patients, physicians and pharmacists. Jariwala et al. [107] described the factors affecting the adoption of e-prescribing system by primary care physicians and their experience with the system in the United States. Kaushal et al. [108] found e-prescriptions reduce a significant amount of prescribing errors in compare with handwritten prescriptions. Fernando et al. [109] studied how electronically delivered prescriptions reduced the pharmacy waiting time and improved patient satisfaction. Lapane et al. [110] measured the perception and readiness to accept electronic prescriptions among elderly geriatric patients in six stated in the USA. Smith [111] explored the barriers to accepting e-prescription among general patients in Pittsburgh metropolitan area in the USA. Kierkegaard [104] examined the prospects and problems concerning the cross-border use of e-prescription among 27 member countries of European Union. Ateniese et al. [112] studied the issues related to privacy of medical data in e-prescription. However, not enough studies were conducted to explore and quantify the factors that affect rural patients' compliance with e-prescription, especially from the perspective of Asian developing countries where most of the world's population resides. Therefore, the objectives of this section of the study are:

i. To measure the level of patients' trust by assessing their e-prescription compliance behavior.
ii. To identify the factors with relative significance that affect rural patients' primary compliance with e-prescription.

4.3 Methods

In order to achieve the research objective, we have selected five socio-demographic factors i.e. age, gender, education, purchase power and use of cellphone based on existing literature relating to patients' primary compliance with prescriptions. Several studies [96], [113]–[117] confirmed the profound impact of patients' socio-demography on their primary compliance with prescribed medication. Patel et al. [118] found a positive correlation between drug adherence and physician visiting frequency which motivated us to check whether there is any significant relationship between patients' visiting frequency of PHC and their primary compliance with the prescription. Syed et al. [119] examined the relationship between medication compliance and distance to pharmacy and prescriber which reinforced us to add one more variable to our research framework. However, in this study, we have employed a total of seven independent variables to measure their impacts and magnitudes on rural patients' primary compliance with e-prescription which is shown as our research framework in Figure 4.2.

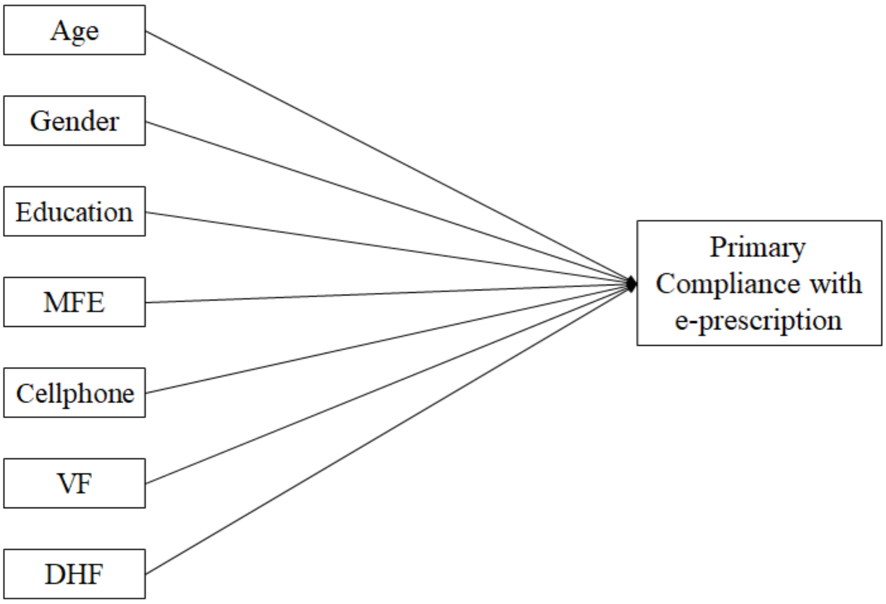


Figure 4.2 Research framework

MFE = Monthly family expenditure; VF = Visiting frequency; DHF = Distance to healthcare facility.

From the above framework, keeping the research objective in mind, we have developed the following seven research hypothesis to be tested:

H1: Patients' age has a positive impact on primary compliance with e-prescription

H2: Patients' gender significantly affects their compliance behaviour

H3: Level of education has a positive influence on patients' primary compliance with e-prescription

H4: Patients' monthly family expenditure affects their primary compliance with e-prescription

H5: Patients' use of cellphone has a significant impact on their compliance behaviour

H6: Visiting frequency has a positive impact on the patients' primary compliance with e-prescription

H7: Distance to healthcare facilities has a significant impact on primary compliance with e-prescription

In order to test the research hypotheses, data were collected through a field survey between June and July 2016 from Bheramara sub-district of Kushtia, a North-Western district of Bangladesh. A structured questionnaire was developed initially in English, which later, was translated into Bengali (the local language of Bangladesh). The survey questionnaire mostly covered the patients' socio-demographic information, their awareness and usage of e-health including usage frequency and finally their compliance behavior towards e-prescription. A pilot study was conducted on seven randomly selected 18+ rural patients to test the understandability of the questionnaire. Their feedback was considered to review the questionnaire. To maintain the right of privacy of the respondents, they have been briefed on the research purpose and asked whether they want to participate in the survey and allow us to use their responses in our scientific publications.

Since the dependent variable in this study is 'compliance with e-prescription' and the response is categorized in either 'Yes' or 'No', thus, we are dealing with a binary classification problem. Several studies [120]–[122] suggested binary logistic regression fits better in this circumstance. Therefore, we also chose binary logistic regression model to test our research hypotheses. Beleites et al. [123] suggested a minimum sample size of 75 to 100 to have a good but not perfect classifier model based on logistic regression. Figueroa et al. [124] examined a total of 568 supervised learning based classification models and found models with sample size between 80 and 560 achieved optimum performance. According to Peduzzi et al. [125] and Kenny [54], in behavioral science with multivariate analysis the, sample size should be at least 10 times the number of items (independent variables) in the study. In our study, the model consists of 7 items and the effective sample size is 95 which is well supported by the studies mentioned above. In order to reach our targeted sample size, we randomly approached 592 rural respondents in our study area among which 355 were found unaware of PHC and thus eliminated. Among the rest 237 respondents who were aware of PHC, 45 found non-users and thus eliminated. Therefore, a total of 192 respondents were found who received healthcare services from PHC at least once. However, 95 (49%) patients out of 192 were reported to receive e-prescription from the remote doctor, thus, in this research, our effective sample size is 95. The sample selection process is shown in Figure 4.3.

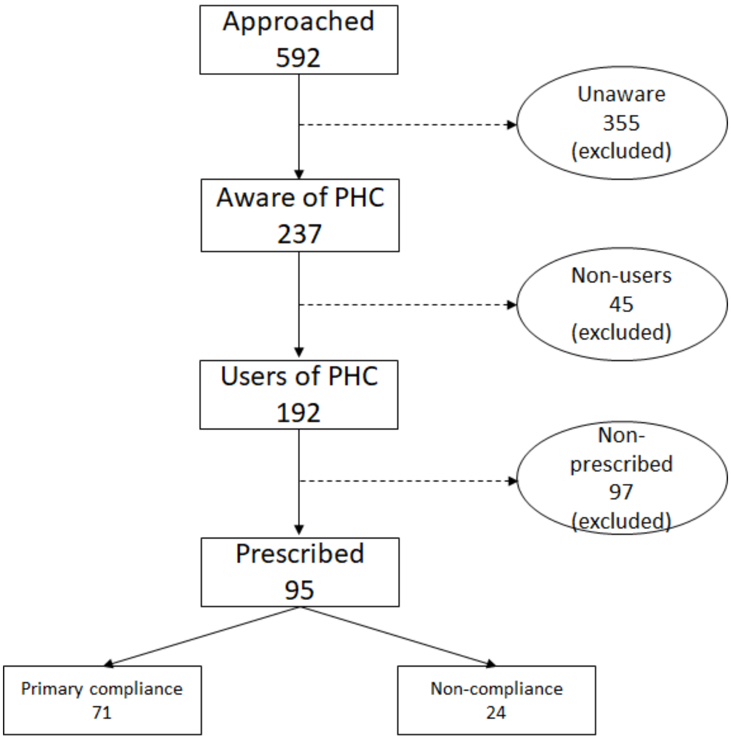


Figure 4.3 Steps in sample selection

4.4 Results

4.4.1 Respondents' Demography

Respondents' demographic characteristics are shown in Table 4.2.

Table 4.2 Respondents' demography (n = 95)

	Frequency	Percentage
Gender		
Male	62	65.0%
Female	33	35.0%
Age group		
<30	19	20.0%
30-45	43	45.5%

46-60	26	27.5%
>60	7	7.0%
Education		
None	15	15.8%
Primary	25	26.3%
Secondary	38	40.0%
College & Higher	17	17.9%
Monthly family expenditure (in BDT)		
<10,000	43	45.3%
10,001 – 15,000	40	42.1%
>15,000	12	12.6%
Use of cellphone		
No phone	16	16.8%
Feature phone	65	68.4%
Smart phone	14	14.8%
Compliance with e-prescription		
Yes	71	74.7%
No	24	25.3%

BDT = Bangladeshi taka (the local currency of Bangladesh).

The above table shows the distribution of dependent variable i.e. patients' compliance with e-prescription, 74.7% was found compliant who reported collecting all the prescribed medicines while 25.3% was found non-compliant. The table also shows the descriptive statistics of five independent variables i.e. age, gender, education, family expenditure and use of cellphone. However, we have two more independent variables in this model i.e. PHC visiting frequency and distance to healthcare facility. The median visiting frequency per patient is 2 with a range of 1 to 10. The mean distance from patient's place to the nearest conventional healthcare facility is 3.3 km. with a standard deviation of 2.3 km.

4.4.2 Correlation among Independent Variables

Pearson correlation analysis is conducted to test whether any multicollinearity exists among independent variables before moving them to the final model which is shown in Table 4.3.

Table 4.3 Correlation matrix of independent variables

	Age	Gender	Edu	MFE	CellPh	PVF	DHF
Age	1						
Gender	0.32	1					
Education (Edu)	-0.18	0.29	1				
Monthly family expenditure (MFE)	0.09	0.32	0.33	1			
Use of cellphone (CellPh)	-0.39	0.16	0.35	0.22	1		
PHC visiting frequency (PVF)	-0.03	0.31	0.14	0.27	0.19	1	
Distance to healthcare facility (DHF)	-0.09	0.18	0.24	0.16	0.14	0.23	1

The matrix shows no multicollinearity exists among independent variables since all the correlation coefficients are less than 0.40 which was referred as a threshold value by many researchers [86].

4.4.3 Results of Hypothesis Testing

A logistic regression modelling is used to test the hypothesis. A significance level of 0.05 is considered for this model. Decisions regarding hypothesis testing have been made by comparing the variables' P-value with models' significance level. Regression coefficient indicates the nature of the relationship between independent and dependent variable while odds ratio explains the magnitude of the effect of independent variables on the dependent variable. The results of hypothesis testing are shown in Table 4.4.

Table 4.4 Results of hypothesis testing through logistic regression

H.	Variable	Coef.	OR	95% CI	P-value	Result
1.	Age	-0.390	0.6769	(0.2219, 2.0651)	0.486	Not Supported
2.	Gender (male)	2.017	7.5134	(1.0773, 52.3988)	0.032	Supported
3.	Education	0.921	2.5120	(0.9648, 6.5399)	0.041	Supported
4.	Monthly family expenditure	1.106	3.0225	(0.6165, 14.8196)	0.152	Not Supported
5.	Use of cellphone	0.334	1.3971	(0.2784, 7.0109)	0.685	Not Supported
6.	PHC visiting frequency	0.994	2.7024	(0.8340, 8.7559)	0.042	Supported
7.	Distance to healthcare facility	0.815	2.2595	(1.1300, 4.5183)	0.006	Supported

Coef. = Regression coefficient; OR = Odds ratio; CI = Confidence interval.

The finding says patients' gender, level of education, PHC visiting frequency and distance to healthcare facility have significant influences on their primary compliance with e-prescription while age, monthly family expenditure and use of cellphone were found insignificant. Male are 7.5 times more likely to comply with e-prescription than female. Education has a positive correlation with compliance, higher educated patients are 2.5 times more likely to comply. Visiting frequency also has a positive impact, every one additional visit to PHC increases the patients' compliance likelihood by 2.7 times. Finally, distance matters, every 1 km. of additional distance between patients' house and the conventional healthcare facility increases the likelihood of e-prescription compliance by 2.2 times.

4.4.4 Model summary and goodness-of-fit

Our model has a deviance R^2 of 0.594 which means the model explains 59.4% of the deviance in the response variable. For binary logistic regression, the 'Hosmer-Lemeshow' test is a more trustworthy indicator of how well the model fits the data [87]. In this model, the goodness-of-fit score is 0.99 which is greater than the significance level of 0.05, which indicates that there is not enough evidence to conclude that the model does not fit the data.

4.5 Discussion and Limitations

A recent study conducted by Raebel et al. [126] on 12,061 hypertension, diabetes, and lipid disordered patients found that e-prescription reduced the primary non-compliance rate from 22% to 13% in comparison with handwritten prescriptions. Fernando et al. [109] found 12.5% primary non-compliance with e-prescription among 224 emergency department patients. However, in this study, we found 25.3% primary non-compliance with e-prescription. This discrepancy exists since partner pharmacies have not yet been incorporated into the PHC system. According to a report by Boston Consulting Group, the electronic transmission of a prescription to a pharmacy increases the possibility of picking up by the patient. It reduces the patient's obligation of providing the prescription to the pharmacy, a problem cited by more than one-third of patients who either forgot to drop it off or had difficulty doing so [127]. This study found male patients to be more compliant with prescription which is consistent with some previous studies [117], [128]–[130], while some studies suggested otherwise [131], [132]. This difference in terms of prescription compliance by gender in rural Bangladesh exists because most of the rural female are unemployed house-makers who have less mobility and more financial dependency on their male counterparts [94]. Several studies [133]–[136] found patients with higher educational level have higher propensity to comply with their prescriptions which resembles our finding too. Innately, it is expected that patients with higher educational level should have better understanding and knowledge about their health, disease, and treatment and therefore be more compliant [114].

The outcomes of the study were based on patients' self-reporting through a questionnaire survey which might have some response bias. Moreover, the time gap between being prescribed and answering the questionnaire may have allowed for recall bias. The study was conducted on a particular geography, thus, concerns may arise about generalization. Further research, therefore, can be carried out by covering a broader geography and adding a few additional independent variables such as patient-prescriber relationship, patients' trust and attitude towards the system, distance between patients' house and drugstores etc. to have more comprehensive insights.

4.6 Conclusion

Primary compliance with prescription, in healthcare, is a vital issue since non-compliance causes unexpected delay in health recovery along with financial and social burdens on patients. The study found patients' gender, education, visiting frequency to care provider and distance to healthcare facilities are strongly associated with their compliance behavior, while their age, monthly family expenditure and use of cellphone were found insignificant. The findings of this study are expected to be helpful for e-health service providers to gain a better understanding of the factors that influence their patients to comply with e-prescriptions.

Chapter 5: Predicting Consumer Behavior

5.1 Introduction

"Knowing who your customers are is great, but knowing how they behave is even better." – Jon Miller

The quote concisely describes why it is critical for every producer and provider to predict consumer behavior. Since consumer needs, situations, perceptions and expectations are constantly changing and evolving, there would be no way to understand them beyond 'today' without some manner of predicting consumer behavior. The good news is that predicting customer behavior is easier now than ever before. With technology, artificial intelligence, big data, algorithms, and predictive analytics we can now predict consumer behavior quite accurately.

Without predicting consumer behavior, companies would come up with offerings and solutions that they 'believe' would be best for customers. However, all the resources, time, and money would be of no use if customers don't need or like the offerings the company produced based on its assumptions. With resources already limited, such wastage could quickly lead to severe losses and irreparable damage to the company. It would be better for companies to refine their strategies and create their offerings by predicting customer behavior [137], [138].

If the eHealth technology developers and service providers can predict their consumer purchase behavior in advance, they will be able to fine-tune the technology and service in accordance to the needs and preferences of consumers. This will also enhance the possibility of large-scale technology adoption in the long run. In this section, we are going to predict consumer's (i.e. patients') eHealth acceptance behavior through supervised machine learning algorithms and recommend the best prediction model in terms of predictive accuracy.

5.2 Background and objective

Machine learning algorithms have been extensively using since the last two decades to build predictive models in agriculture [139]–[142], insurance and banking [143], [144], online shopping [145]–[148], travel and tourism [149], [150], marketing and consumer behavior [151]–[153], healthcare and medical science [154]–[157] along with many other industries. Calvert et al. [151] described how advanced machine learning systems can be used to predict consumer behavior. Emtiyaz et al. [152] used semi-supervised machine learning method to facilitate the CRM process. Cui et al. [153] explained how machine learning algorithms can be used to predict consumers' response to direct marketing. Chen et al. [154] utilized naive bayes, k-nearest neighbour and decision tree algorithms to predict chronic disease outbreak in disease-frequent communities. Ahmad et al. [155] applied decision tree, support vector machine, and artificial neural network to predict breast cancer recurrence. Reddy et al. [156] used gradient boosting machine, regularized regression, and logistic regression to predict inflammation in Crohn's disease patients. Lynch et al. [157] predicted lung cancer patient survival via supervised machine learning algorithms. Machine learning was also used in eHealth for analyzing patient's health data, predicting diseases, enhancing the productivity of technology or devices used for service providing, and so on [158], [159]. However, a very few studies [160]–[162] was found to predict the usage of eHealth among its target patients. Most of these existing studies explain factors that influence eHealth usage by applying technology acceptance model (TAM) or its related models analyzed with conventional statistical methods such as logistic regression, partial least square (PLS) method and structural equation modeling (SEM) etc. On top of that, these studies are mostly conducted from the perspective of developed countries such as European, Central and North American countries. To the best of our knowledge, no study has been conducted so far to predict rural patients' use of eHealth through machine learning predictive analytics, especially from the perspective of under-developed or developing countries where it is mostly needed.

Therefore, the objective of this study is to predict rural patients' use of eHealth via supervised machine learning algorithms and propose the best-fitted model after evaluating their performances.

5.3 Methods

To attain the research objective we followed several steps in our research methodology which is shown in Figure 5.1.

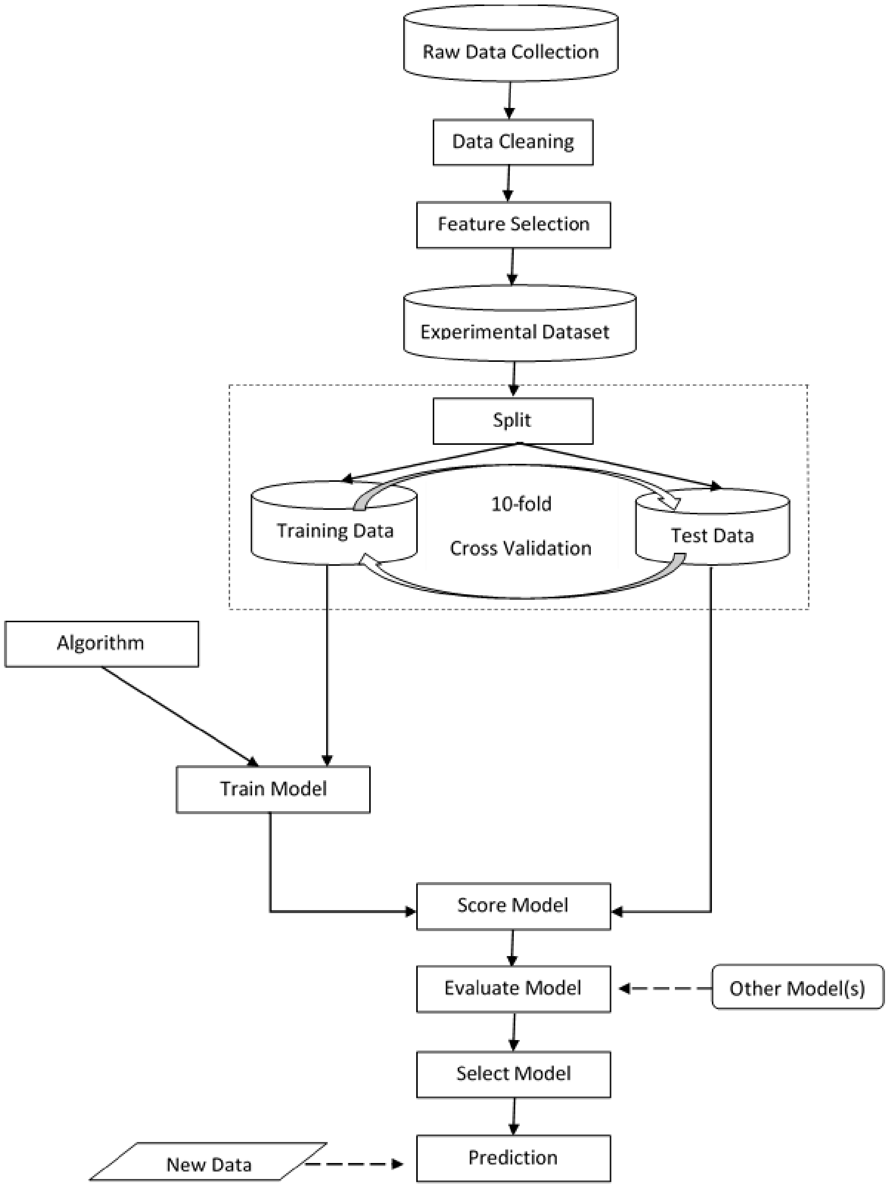


Figure 5.1 Research Methodology

5.3.1 Sampling and data collection

Data were collected between June and July 2016 through a field survey based on a structured questionnaire. The survey was conducted in Bheramara sub-district of Kushtia, a North-Western district of Bangladesh where PHC is serving since 2012. Close-ended questions were used to extract respondents' demography and a five-point Likert-scale from extremely disagree to extremely agree with a neutral point on 3 was used to extract the cognitive variables. The questionnaire was prepared initially in English and later was translated to Bengali (the local language of Bangladesh). A pilot study was conducted on 7 randomly selected 18+ rural patients to assess the understandability of the questionnaire. Their feedback was considered to review the questionnaire. To maintain the right of privacy of the respondents, they have been briefed on the research purpose and asked whether they want to participate in the survey as well allow us to use their response in our scientific publications.

A total of 592 questionnaire was distributed randomly, however, after removing unsuitable cases due to missing fields and partially answered questionnaires, we could include 292 respondents as our effective sample size to carry forward with. The sample was drawn by a simple random sampling method which eliminates the bias by giving all individuals an equal chance to be chosen [51]. Beleites et al. [123] suggested a minimum of 75 to 100 samples per class is required to have a good but not perfect classifier. Figueroa et al. [124] examined a total of 568 supervised learning based classification models and found models with sample size between 80 to 560 achieved optimum performance. We, therefore, consider 292 as a moderately optimum sample size for our study.

5.3.2 Feature selection

In predictive modeling, feature selection is required to minimize redundancy and computational effort while maximizing prediction accuracy by keeping the most relevant but not redundant features [163]. M. Hall [164] suggested 'correlation-based feature selection' as one of the most widely used and easy-to-explain methods for machine learning classification model. In this study, we have selected 12 features out of 14 based on their correlation coefficient (r) with the dependent variable and level of significance (P-value).

5.3.3 Selection of algorithms

Since our dependent variable is eHealth use and the response is either ‘Yes’ or ‘No’, thus, we are dealing with a binary classification problem. Existing studies [165]–[168] suggest logistic regression, boosted decision tree, support vector machine, and artificial neural network algorithms perform better in binary classification. In our study, therefore, we selected the four aforementioned machine learning algorithms to predict eHealth usage among rural consumers in Bangladesh.

5.3.4 Cross-validation

Cross-validation method is one of the most frequently used techniques in predictive modeling to reduce bias and over-fitting which is commonly known as misclassification error. In this study, we applied a 10-fold cross-validation method to evaluate the validity of present results and to make predictions from unobserved new data. In this method, each of the 10 subsets acts as an independent holdout test set for the model trained with the rest of the subsets. A pair of testing and training sets is called a ‘fold’. Borra et al. [169] and Kohavi [170] suggested 10-fold cross validation is an optimal method to reduce bias and over-fitting of the data. Figure 2 shows increasing the number of subset (fold) up to 10, the misclassification error reduces significantly. However, after 10 it become stabilized or even in some cases it may slightly increase. It is, therefore, recommended by many researchers to follow 10-fold cross validation method to reduce misclassification error or overfilling.

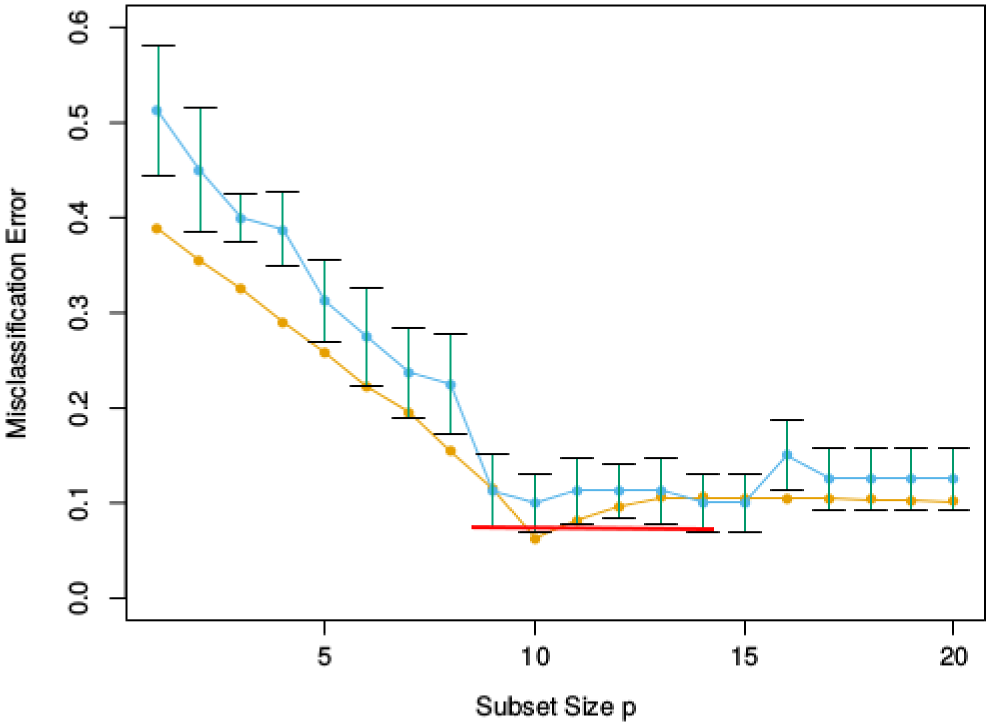


Figure 5.2 Optimum subset for cross-validation

[Source: R. Kohavi, "A Study of Cross-Validation and Bootstrap for Accuracy Estimation and Model Selection," *Proc. Int. Jt. Conf. Artif. Intell.*, vol. 14, no. 2, pp. 1137–1145, 1995.]

5.3.5 Performance evaluation

Existing studies [171], [172] suggest five most commonly used indexes namely, Accuracy, Precision, Recall, F-Score, and AUC to evaluate the performance of binary classifiers. We, therefore, adopted those aforementioned five indexes to evaluate and compare model's performance in our study. The indexes can be calculated according to the figures in Table 5.1 and the following formulas, respectively.

Table 5.1 Contingency table for performance evaluation

	Actual Positive	Actual Negative
Predicted Positive	TP	FP
Predicted Negative	FN	TN

TP, true positive; FP, false positive; FN, false negative; TN, true negative

- **Accuracy** measures the overall effectiveness of a classification model as the proportion of true results to total cases.

  (TP+TN) / (TP+FP+TN+FN)

- **Precision** measures the proportion of true results to all positive results.

  TP/(TP+FP)

- **Recall** measures the effectiveness of a classifier to identify positive results.

  TP/(TP+FN)

- **F-score** is computed as the weighted harmonic mean of precision and recall between 0 and 1, where the ideal F-score value is 1.

  2 (precision x recall) / (precision + recall)

- **AUC** measures the classifier's ability to avoid false classification. The area under the curve (AUC) is plotted with true positives on the y-axis and false positives on the x-axis. This metric is useful because it provides a single number that lets you compare models of different types. When the area is closer to 1, the model is better.

  ½ {TP/(TP+FN)+TN/(TN+FP)}

We performed the experiment using Microsoft Azure Machine Learning Studio, a cloud-based computing platform that allows to build, test, and deploy predictive analytics solutions [173]. Figure 5.3 shows the machine learning model which is used for this experiment.

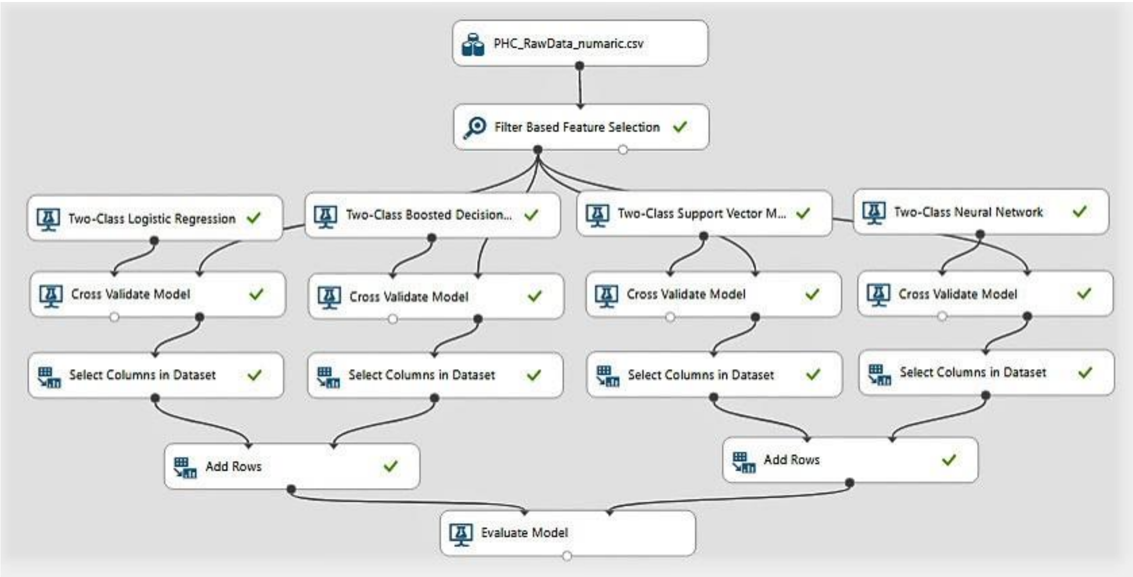


Figure 5.3 Predictive Model in Microsoft Azure ML Studio

In this experiment, at first, we coded the raw data into numeric form then applied correlation-based feature selection module to keep the most relevant but not redundant features into the model. Four supervised machine learning algorithms namely logistic regression, boosted decision tree, support vector machine, and artificial neural were applied to predict the consumer purchase behavior based on cross-validation method. Finally, the algorithms' performance were measured and compared by five indexes namely, Accuracy, Precision, Recall, F-Score, and AUC.

5.4 Results

5.4.1 Respondents' demography

The respondents' demography is shown in Table 5.2. Beleites et al. [123] suggested a minimum of 75 to 100 observations per classes is required to have a functional binary classifier. To avoid imbalanced dataset, over-fitted accuracy, and sample bias, it is recommended by many recent studies [174], [175] to have almost, if not exactly, equal ratio of observations for both positive and negative responses. In this research, the dependent variable is eHealth use which is labelled by 'Yes' or 'No', and we have 58% (171) positive label and 42% (121) negative label that clearly meets the above standards.

Table 5.2 Sample demographics (n = 292)

	Frequency	Percentage
Sex		
Male	205	70.0%
Female	87	30.0%
Age group		
Less than 30	67	22.9%
30-45	148	50.6%
46-60	64	21.9%
More than 60	13	4.5%
Education		
None	23	8.0%
Primary	72	25.0%
Secondary	114	39.0%
College & Higher	83	28.0%
Monthly family expenditure (in BDT)		
Less than 6,000	31	11.0%
6,001 – 10,000	118	40.0%
10,001 – 15,000	100	34.0%
15,001 – 20,000	30	10.0%
More than 20,000	13	4.0%
Cellphone ownership		
Yes	252	86.0%

No	40	14.0%
eHealth (PHC) use		
Yes	171	58.0%
No	121	42.0%

BDT, Bangladeshi taka (the local currency of Bangladesh).

5.4.2 Feature selection

Initially, we collected data on 14 features/independent variables to predict the use of eHealth as the dependent variable. The proposed set of features is shown in Table 5.3 and later, a correlation-based feature selection technique was applied to select the most relevant but bot redundant features which are shown in Table 5.4.

Table 5.3 The proposed set of variables/features for predictive modeling

Features/independent variables			
No.	Variable	Description	Type
1	Age	Respondent's age	Discrete
2	Sex	Male or Female	Categorical
3	Level of education (Edu)	4 categories from none to college or higher	Categorical
4	Monthly family expenditure (MFE)	5 categories from <6000 BDT to >20000 BDT	Categorical
5	Use of cellphone (Cellph)	Yes or No	Categorical
6	Exposed to PHC advertisements (Ad)	Yes or No	Categorical
7	Having social reference (SR)	Yes or No	Categorical
8	Perceived usefulness (PU)	5 point Likert scale	Ordinal
9	Perceived ease of use (PEU)	5 point Likert scale	Ordinal
10	Perceived privacy (PP)	5 point Likert scale	Ordinal
11	Perceived cost (PC)	5 point Likert scale	Ordinal
12	Service delivery time (SDT)	5 point Likert scale	Ordinal

13	Service quality (SQ)	5 point Likert scale	Ordinal
14	Result demonstrability (RD)	5 point Likert scale	Ordinal
Target/dependent variable			
1	eHealth (PHC) use	Yes or No	Categorical

Table 5.4 Correlation-based feature selection

	Variable/feature						
	PC	PU	PP	RD	SR	SQ	PEU
Correlation coefficient	0.536	0.453	0.445	0.412	0.410	0.395	0.394
P-value	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	Variable/feature						
	SDT	Age	Ad	Sex	Edu	CellPh	MFE
Correlation coefficient	0.377	0.348	0.317	0.197	0.149	0.049	0.010
P-value	0.000	0.000	0.000	0.001	0.011	0.404	0.865

Table 5.4 shows the use of cellphone (Cellph) and respondents' monthly family expenditure (MFE) are having very insignificant correlation coefficients (r) with the dependent variable i.e. 0.049 and 0.010 respectively and P-values are also above the threshold (.05) level i.e. 0.404 and 0.865 respectively. Therefore, we eliminated these two features and proceeded with the rest 12 for our predictive models.

The IPO (input-process-output) model for predicting consumer behavior based on 12 selected features is shown in Figure 5.4

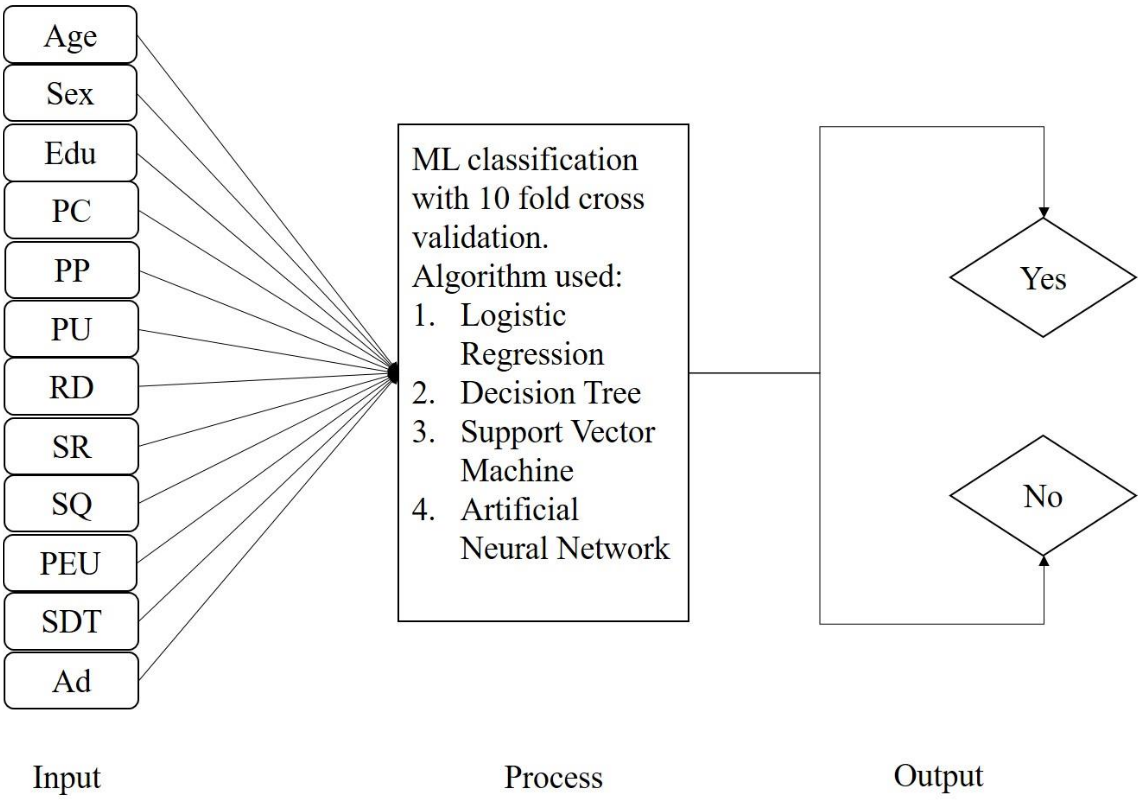


Figure 5.4 The IPO model for prediction

5.4.3 Model performance

5.4.3.1 Accuracy

For our experiment, we selected four supervised machine learning algorithms namely, logistic regression, boosted decision tree, support vector machine, and artificial neural network based on existing literature [165]–[168] review related to binary classification. A 10-fold cross-validation technique was applied to evaluate and compare the performance of models which is shown in Table 5.5 and Figure 5.5.

Table 5.5 Cross-validate accuracy

		Accuracy			
Round of experiments	Cumulative observations in the test set	Logistic Regression	Decision Tree	SVM	Neural Network
1	30	86.7%	83.3%	86.7%	90.0%
2	59	89.9%	83.0%	84.7%	88.1%
3	88	87.5%	80.7%	79.5%	84.0%
4	117	90.6%	82.9%	82.0%	87.2%
5	146	86.3%	81.5%	80.1%	83.5%
6	175	85.7%	81.7%	79.4%	84.0%
7	204	84.8%	82.3%	79.9%	83.3%
8	233	85.4%	83.7%	79.4%	83.7%
9	262	85.5%	83.6%	79.7%	83.6%
10	292	85.9%	82.9%	80.4%	84.2%

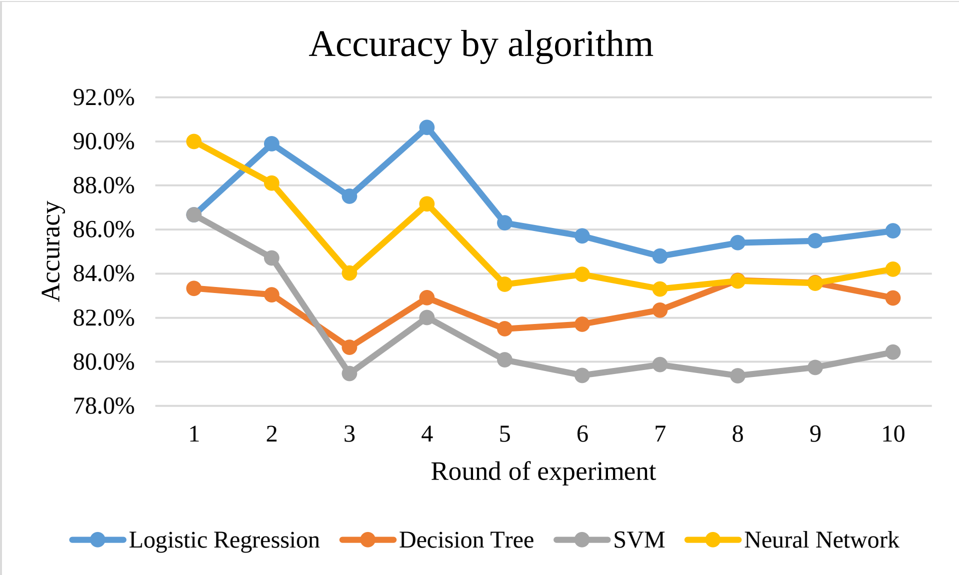


Figure 5.5 Accuracy by algorithm

The finding shows, logistic regression outperforms other models with an accuracy rate of 85.9% followed by neural network 84.2%, decision tree 82.9% and support vector machine 80.4% respectively.

5.4.3.2 Precision

Table 5.6 Cross-validate precision

		Precision			
Round of experiments	Cumulative observations in the test set	Logistic Regression	Decision Tree	SVM	Neural Network
1	30	88.2%	83.3%	88.2%	88.9%
2	59	87.9%	79.9%	82.4%	85.1%
3	88	89.5%	81.8%	79.9%	83.8%
4	117	92.1%	86.4%	84.9%	86.5%
5	146	86.7%	83.1%	81.6%	82.2%
6	175	86.7%	83.0%	80.3%	82.4%

7	204	85.6%	83.7%	81.3%	82.4%
8	233	86.2%	85.1%	81.2%	82.8%
9	262	85.9%	84.5%	81.4%	82.9%
10	292	86.4%	85.0%	82.3%	83.7%

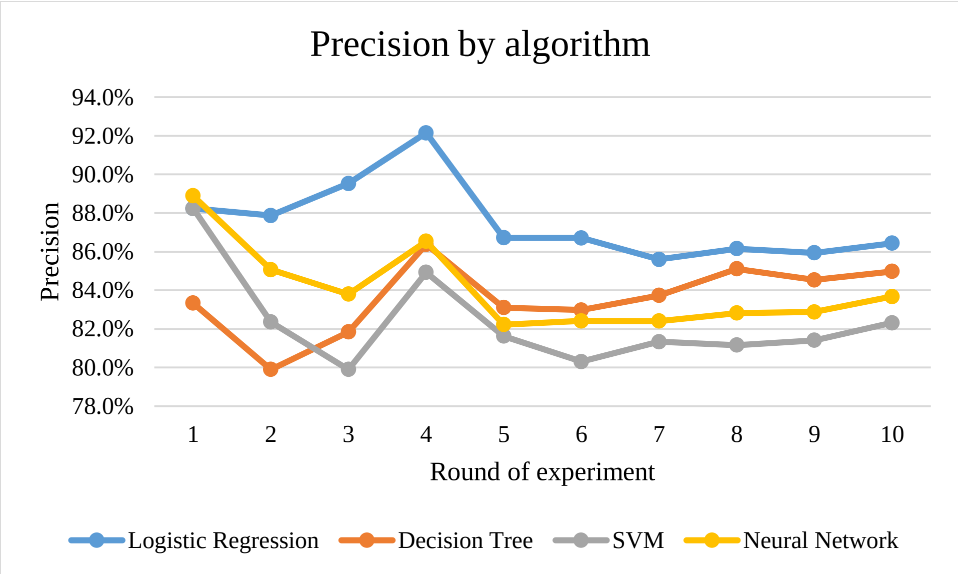


Figure 5.6 Precision by algorithm

5.4.3.3 Recall

Table 5.7 Cross-validate recall

		Recall			
Round of experiments	Cumulative observations in the test set	Logistic Regression	Decision Tree	SVM	Neural Network
1	30	88.2%	88.2%	88.2%	94.1%
2	59	94.1%	90.5%	90.5%	93.5%
3	88	88.2%	83.9%	83.9%	87.8%

4	117	91.2%	83.8%	83.8%	90.9%
5	146	90.3%	85.7%	84.3%	90.0%
6	175	88.8%	86.0%	84.9%	90.6%
7	204	88.7%	86.3%	84.5%	89.5%
8	233	89.4%	87.4%	84.5%	90.1%
9	262	90.0%	88.1%	84.9%	89.9%
10	292	90.5%	86.9%	85.4%	90.4%

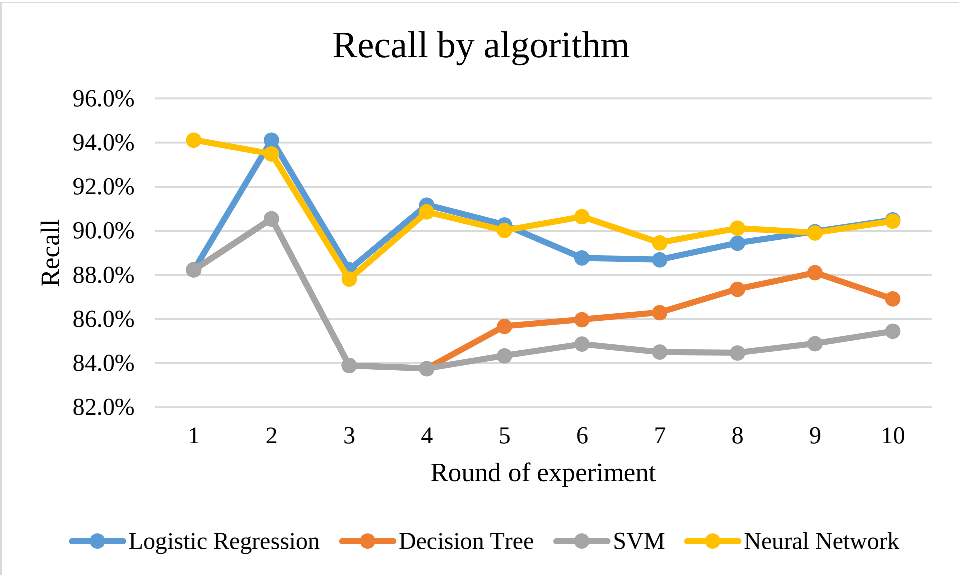


Figure 5.7 Recall by algorithm

5.4.3.4 F-Score

Table 5.8 Cross-validate F-Score

		F-Score			
Round of experiments	Cumulative observations in the test set	Logistic Regression	Decision Tree	SVM	Neural Network

1	30	88.2%	85.7%	88.2%	91.4%
2	59	90.8%	84.8%	86.1%	89.0%
3	88	88.5%	82.3%	81.6%	85.6%
4	117	91.4%	84.5%	83.9%	88.5%
5	146	87.9%	83.6%	82.4%	85.7%
6	175	87.3%	83.8%	82.0%	86.1%
7	204	86.7%	84.4%	82.4%	85.6%
8	233	87.4%	85.7%	82.4%	86.1%
9	262	87.6%	85.8%	82.8%	86.1%
10	292	88.1%	85.4%	83.5%	86.8%

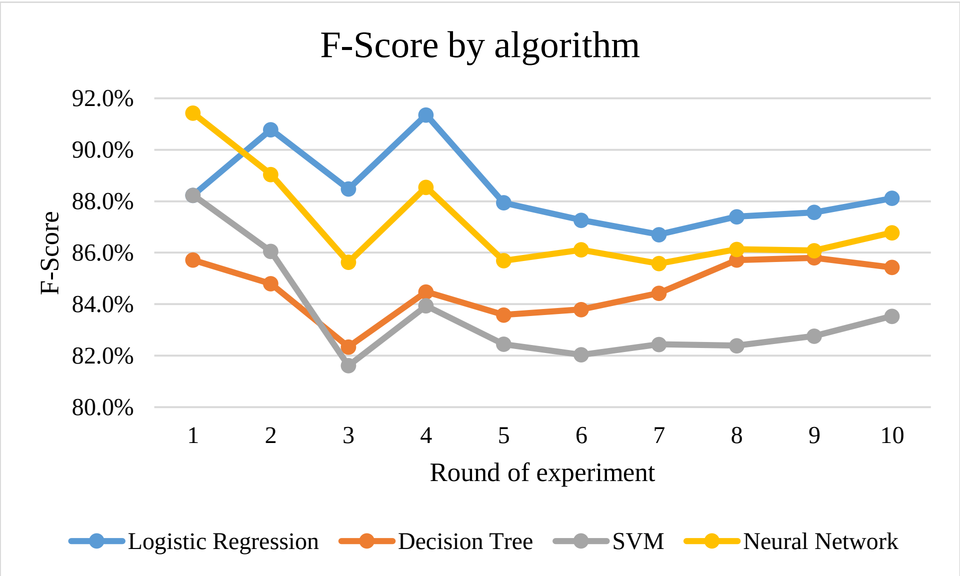


Figure 5.8 F-Score by algorithm

5.4.3.5 AUC

Table 5.9 Cross-validate AUC

		AUC

Round of experiments	Cumulative observations in the test set	Logistic Regression	Decision Tree	SVM	Neural Network
1	30	95.0%	91.0%	93.2%	95.9%
2	59	93.0%	90.7%	90.9%	93.4%
3	88	91.1%	89.4%	86.9%	91.4%
4	117	93.3%	91.2%	89.7%	93.4%
5	146	89.1%	89.4%	85.9%	89.8%
6	175	89.9%	89.7%	86.8%	90.2%
7	204	89.8%	90.1%	86.8%	89.7%
8	233	90.5%	91.0%	86.2%	90.1%
9	262	91.1%	91.5%	86.8%	90.5%
10	292	91.5%	91.3%	87.5%	90.7%

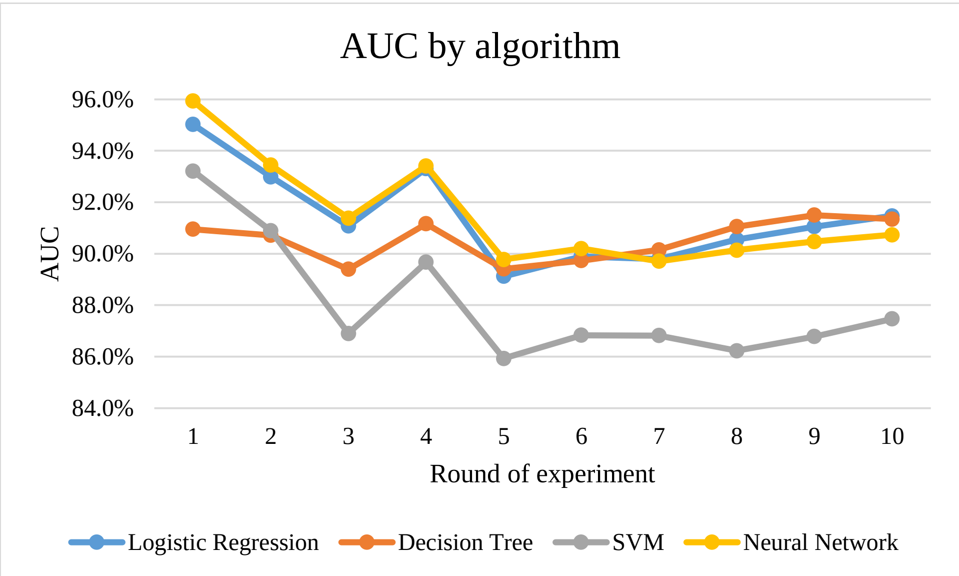


Figure 5.9 AUC by algorithm

5.4.3.6 Overall model performance

Beyond accuracy, there are some other well-known indexes such as precision, recall, F-Score, and AUC to evaluate and compare the overall performance of binary classifiers [171], [172]. In order to have a broader comparative picture of all the models, we applied those indexes into our experiment and the summary results are shown in Table 3.5 and Figure 3.2 while the detailed results are presented in Multimedia Appendix 3.

Table 5.10 Overall model performance

Model	Accuracy	Precision	Recall	F-Score	AUC
Logistic Regression	85.9%	86.4%	90.5%	88.1%	91.5%
Decision Tree	82.9%	85.0%	86.9%	85.4%	91.3%
SVM	80.4%	82.3%	85.4%	83.5%	87.5%
Neural Network	84.2%	83.7%	90.4%	86.8%	90.7%

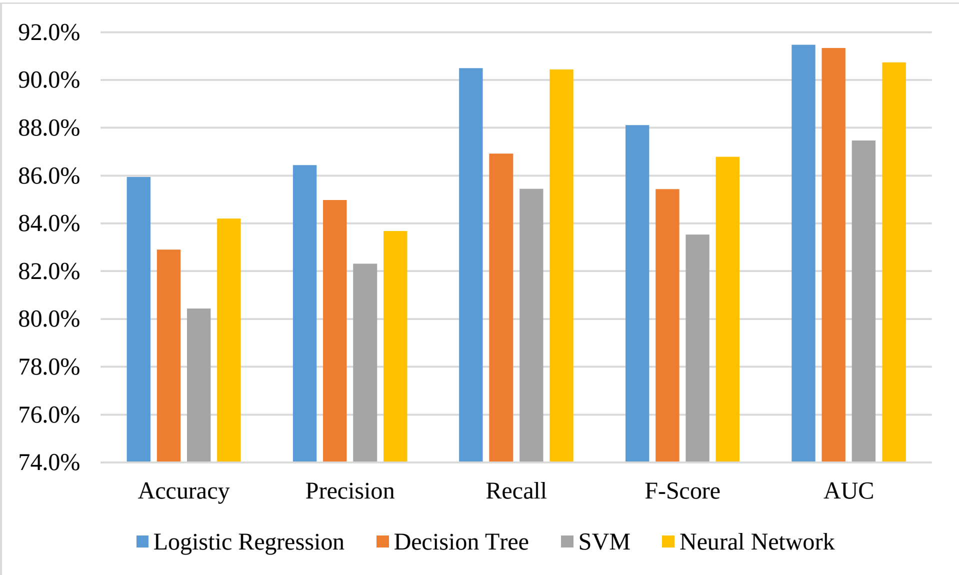


Figure 5.10 Overall performance

The result shows logistic regression again outperforms other models by all the five indexes with an accuracy rate of 85.9%, the precision rate of 86.4%, recall rate of 90.5%, F-score of 88.1%, and AUC of 91.5%.

5.5 Implications

The prediction model can be deployed in two ways: (shown in Figure 5.11)

(1) Offline excel-based deployment where any eHealth service provider can predict its individual consumer's purchase behavior and also group or batch prediction is possible here. However, due to its offline nature, any up-gradation in the algorithm will not be reflected here.

(2) Online web-based deployment where both individual and batch prediction is possible and also any change or up-gradation in algorithm or sample size will be reflected real-time here.

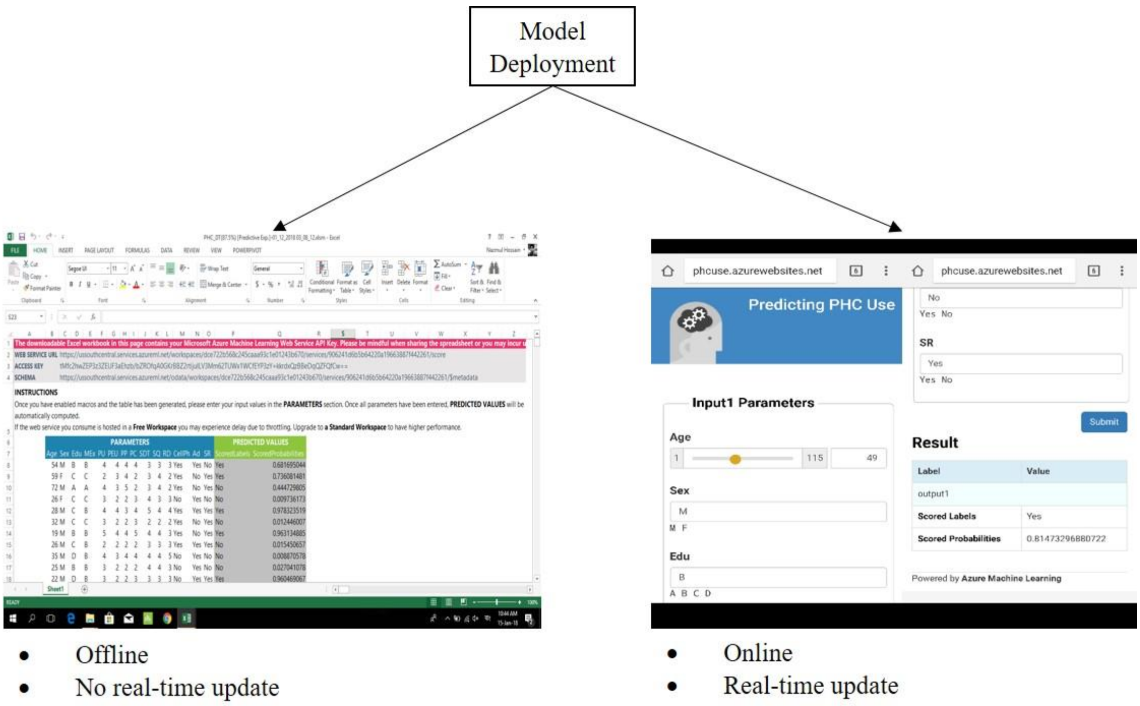


Figure 5.11 Model deployment

This predictive analytics can also be used to identify the best market segment where the likelihood of acceptance of eHealth system is comparatively higher than other segments based on the 12 parameters used in this experiment. A fictitious example is given below to understand the scenario how predicting consumer behavior can help an eHealth service provider to select a more appropriate area to serve.

Let's assume, PHC has two area options to serve: 'Area: A' and 'Area: B'. But due to resource limitation, it has to select any one where the possibility of accepting eHealth will be comparatively higher. As a part of its feasibility study, PHC collected information on the aforementioned 12 parameters from 500 potential users of eHealth from each area and measure their purchase intention by using the prediction model suggested in this study. The distribution of predicted probability of those two fictitious areas are shown in Table 5.11 and Figure 5.12

Table 5.11 Probability distribution by area

Predicted probability	Area: A	Area: B
≤.10	25%	14%
.11-.20	12%	9%
.21-.30	7%	5%
.31-.40	5%	8%
.41-.50	16%	13%
.51-.60	8%	17%
.61-.70	11%	15%
.71-.80	6%	9%
.81-.90	5%	7%
≥.91	5%	3%
Total	100%	100%

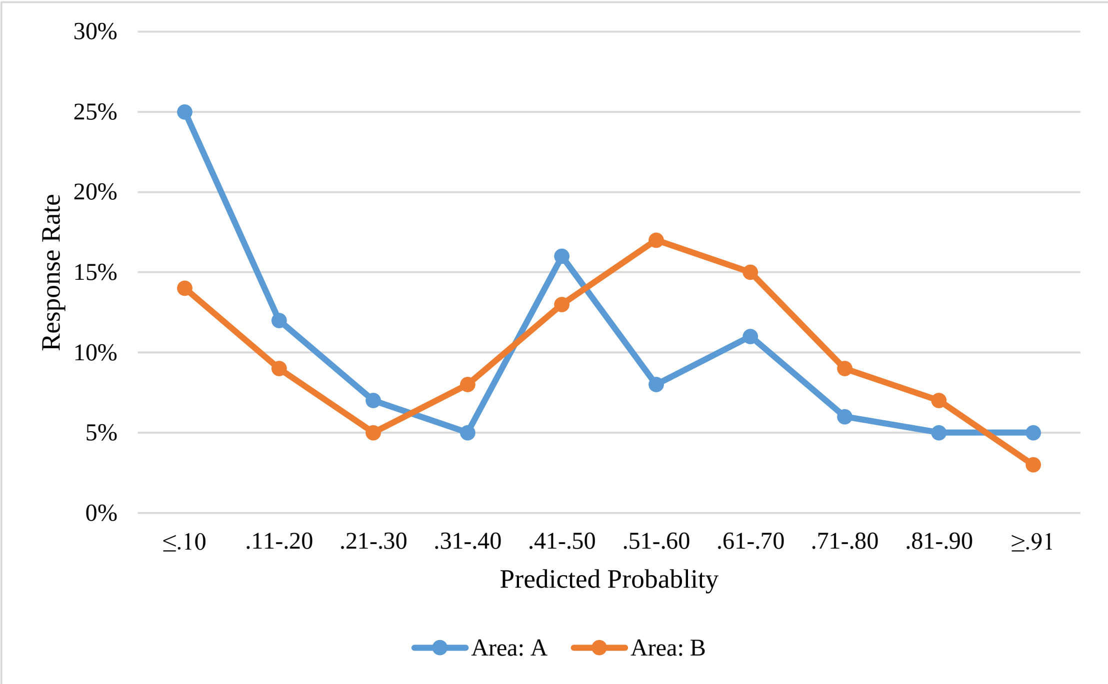


Figure 5.12 Area selection based on predicted probability

Figure 5.8 shows ‘Area: A’ has higher predicted probability in lower threshold (.01-.50) while ‘Area: B’ has higher predicted probability in higher threshold (.51-1.0). Therefore, the service provider should select ‘Area: B’ over ‘Area: A’ due to comparatively higher probability of acceptance.

5.6 Discussion and Limitations

Ahmad et al. [155] found support vector machine with an accuracy of 95.7% followed by artificial neural network with 94.7% accuracy and decision tree with 93.6% accuracy in predicting breast cancer recurrence with a sample of 1189 patients and 22 predictive variables. Gupta et al. applied logistic regression algorithm to predict online customers’ purchase and found an accuracy rate of 88.75%. Reddy et al. [156] found gradient boosting machine more efficient than regularized regression and logistic regression in predicting inflammation in Crohn’s disease patients with AUC = 92.82%. However, in this study, we found logistic regression more effective with accuracy = 85.9%, precision = 86.4%, recall = 90.5%, F-score = 88.1%, and AUC = 91.5% than decision tree, support vector machine, and artificial neural network in predicting rural patients’ use of eHealth with a sample of 292 and 12 predictors. According to Ali and Smith (2006), logistic regression performs well especially when the problem is about binary classification [165]. On the other hand, decision tree, support vector machine, and neural network can be used for both regression and classification including binary and multi-class. However, they are more appropriate when the dataset ensures large volume, variety, and velocity i.e. a very large number of features and observations should exist in the dataset [167], [168].

Although this study has collected and analyzed data from 292 rural respondents in a particular area, the applicability of the presented classifiers in other rural areas remain unknown and thus recommended for future investigation. A natural extension of this research can be conducted by adding some important predictors such as consumers' trust on eHealth and technology anxiety etc. to increase predictive accuracy. Lastly, since patients change their perception very recurrently it would be interesting to do a longitudinal study to measure and compare the findings between different time periods.

5.7 Conclusion

This study has applied four supervised machine learning algorithms to predict rural patients' use of eHealth in Bangladesh. A 'correlation-based feature selection' technique was applied to include the most relevant but not redundant features into the model. A 10-fold cross-validation technique was applied to reduce bias and over-fitting of the data. The performance was measured and compared based on five commonly used indexes for classifiers namely accuracy, precession, recall, F-score, and AUC. Logistic regression was found more effective with a predictive accuracy of 85.9%, the precision of 86.4%, recall of 90.5%, F-score of 88.1%, and AUC of 91.5% followed by neural network with 84.2% accuracy, decision tree with 82.9% accuracy and support vector machine with 80.4% accuracy. eHealth practitioners, by applying the predictive analytics suggested in this study, will be able to predict the potential usage of their services with a certain level of accuracy. Thus, the findings are expected to be helpful for them in selecting more appropriate areas to serve and in proper utilization of available resources by dealing with under-capacity or over-capacity.

Chapter 6: Conclusion and Future Works

6.1 Summary

This study discussed the significance of understanding consumer behavior of eHealth systems especially from the perspective of a developing country like Bangladesh. It explored the current level of knowledge and awareness of eHealth among rural consumers. We found approximately 40% of the rural respondents have knowledge about using ICT in obtaining healthcare services while 32% have their own experience of receiving eHealth care services from PHC. The study has also identified the major reasons for using PHC which include affordable price (30.3%), faster service (29.7%), and opportunity of virtual consultation with specialist doctors (18.8%). On the other hand, the major reasons for not using PHC include lack of consumer's readiness to switch from conventional healthcare platform to e-Health (38.2%), the irregular presence of PHC (16.6%), and lack of knowledge on eHealth (13.5%).

The study also identified the factors with their relative magnitudes that affect consumer acceptance of eHealth and found social reference as the most significantly influential variable (Coef.=2.28, OR=9.73, $p<0.01$) followed by advertisement (Coef.=1.94, OR=6.94, $p<0.01$); attitude towards the system (Coef.=1.52, OR=4.56, $p<0.01$); access to cellphone (Coef.=1.37, OR=3.92, $p<0.05$) and perceived system effectiveness (Coef.=0.74, OR=2.10, $p<0.01$). With these findings, we came up with an extended 'eHealth acceptance model' which will assist eHealth system developers and service providers to achieve large-scale adoption of eHealth among rural communities in developing countries.

Next, we identified the factors that affect rural patients' primary compliance with e-Prescriptions and found patients' gender, education, visiting frequency to care provider and distance to healthcare facilities are strongly associated with their compliance behavior, while their age, monthly family expenditure and use of cellphone were found insignificant.

Finally, we propose a prediction model based on machine learning algorithms to predict consumers' purchase behavior in advance.

The major contributions of this research are mentioned in the next section.

First, this research proposed an extended eHealth acceptance model for rural end-users which performs slightly better (by 2%) than the existing TAM related models with an R2 of 0.54 and adjusted R2 of 0.51.

Second, we proposed a new mechanism of measuring patients' trust towards remote healthcare systems by assessing their e-prescription compliance behavior instead of asking simple binary or Likert scale questions. The study found 74.7% primary compliance among the users. We also found the prime factors with their relative magnitudes that affect the patients' compliance behavior.

Third, we have developed a prediction model based on machine learning algorithms which can predict consumers' usage behavior with an accuracy of 89.5%, precision of 86.4%, recall of 90.5%, F-score of 88.1%, and AUC of 91.5% through 12 predictive variables.

The findings of this research are expected to be helpful for eHealth system developers and service providers to gain a comprehensive understanding of the factors that affect the end-users' or consumers' acceptance of remote healthcare service. Therefore, they can redesign their technologies and services in accordance with the requirements and preferences of their target consumers. As a consequence, large-scale social adoption and long-run sustainability of eHealth systems will be achieved. The findings will also help to increase the level of e-prescription compliance among rural patients, therefore the overall morbidity is expected to be reduced. Finally, the machine learning prediction model will assist the service providers to select more appropriate users and areas to be served with limited resources with a certain level of accuracy and precision.

6.2 Future Works

Since this study was conducted on a particular geography, the results may raise concerns about the generalization of the findings. Further research, therefore, should be carried out covering broader geography.

A few additional variables could be added to the proposed eHealth acceptance model such as compatibility, technology anxiety, and resistance to change to gain more comprehensive insights of eHealth acceptance by rural end-users.

We also believe, further longitudinal studies can be performed to observe the changes in relational pattern and strength of input variables with eHealth acceptance. Consumer behavior has an ever-changing phenomenon and this is why their perceptions and attitude towards eHealth systems may change over times. It is, therefore, necessary to conduct a longitudinal or time-series study to measure the fluctuations in behavior.

Acknowledgements

A doctoral student does not voyage alone in the pursuit of knowledge. The inspiration and support of many individuals have guided me from an idea to a completed dream.

I would like to express my heartiest gratitude to my academic supervisor, Dr. Ashir Ahmed for his insight and dedicated support throughout my research. To my committee members, Dr. Fumihiko Yokota, Dr. Kenji Hisazumi and Professor Akira Fukuda for their supportive guidelines.

I would also like to thank Grameen Communications, Bangladesh for helping me in data collection and Toyota Motor Corporation, Japan for funding the Portable Health Clinic project which I utilized as my experimental research field.

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Appendix

Appendix 1: Survey questionnaire

Name: Age:

Sex: Contact No.: Occupation:

1. Do you have a mobile phone?
   a) Yes
   b) No

   (If the answer is "Yes":)
   1.1.What kind of phone you have?
      a) Feature phone
      b) Smartphone
      c) Both

   (If the answer is "Smartphone":)
   1.2 Do you use internet in your smartphone?
      a) No
      b) ≤ 1 year
      c) 1 – 3 years
      d) 3 – 5 years
      e) ≥ 5 years

2. Does anyone of your family have a mobile phone?
   a) Yes
   b) No

3. Education:
   a) None
   b) Primary
   c) Secondary
   d) College and higher

4. Monthly family expenditure (in TK.):
   a) Less than 6000
   b) 6001 – 10000
   c) 10001 – 15000

   d) 15001 – 20000
   e) 20000+

5. Do you have any idea that, ICT (mobile phone, laptop computer, internet network) can be used to obtain healthcare services (like health check-up, consulting with doctors, obtaining prescription etc.)?
   a) Yes
   b) No

6. In your opinion, what could be the possible use of ICT in healthcare? (Answers can be **multiple**)
   a) Knowing availability of doctors
   b) Setting appointment
   c) Direct consultation
   d) Clarification about prescription
   e) Requesting home visit
   f) Others (…………………………..)

7. Have you ever used any of the services mentioned above (in Q-6)?
   a) Yes
   b) No

8. Do you know about healthcare services provided by PHC in your area? (Answer should be **one** only)
   a) No, I have never heard about PHC
   b) Yes, I have heard about PHC but never seen
   c) Yes, I know about PHC and I have seen someone else taking service from PHC
   d) I myself have experienced PHC service
   e) I have recommended my family or friends to take service from PHC
   f) I have taken services from PHC and recommended others to take

9. Where from you came to know about PHC?
   a) From my friends or family
   b) Local discussion in hat-bazar
   c) From PHC's promotional campaign
   d) From someone who received PHC service
   e) By seeing PHC establishment

10. Have you ever received healthcare service from PHC?
   a) Never
   b) Only 1 time
   c) More than 1
   d) Mention if you remember (……….) times

11. Have you fallen sick in last 6 months or recent past?
    a) Yes
    b) No

12. What do you usually do when you get sick? (Answers can be **multiple**)
    a) Visit local village doctor
    b) Visit Thana Health Complex
    c) Visit homeopath doctor
    d) Visit PHC
    e) Rely on ayurvedic treatment
    f) Kobiraz / Jhar-fuk
    g) Did nothing but wait to be naturally recovered
    h) Other (…………………………………………………………)

    12.1. Do you go for health checkup even if you are not sick?
        a) No, never
        b) Sometimes
        c) Yes, regular

13.1) What is the distance between your home and traditional healthcare center?
Ans.: …………… km.

13.2) What is the distance between your home and nearest PHC?
Ans.: …………… km.

(Q-14 is only for those who answered (a), (b) or (c) in response to Q-12)

14. What did you do after getting the prescription from a doctor?
    a) I bought all the drugs according to the prescription
    b) I bought some of the drugs but not all
    c) I didn't buy any drug

(Q-15 & 16 is only for those who already used PHC)

15. What did you do after getting the prescription from PHC?
    a) I bought all the drugs according to the prescription
    b) I bought some of the drugs but not all
    c) I didn't buy any drug

16. Reasons of using PHC:
    a) Easy access
    b) Time saving
    c) Less costly than conventional
    d) Consult with specialist doctor

e) After getting positive reference from others
f) Being influenced by PHC's promotional campaign
g) Wanted to try something new
h) Others (……………………………………………………………)

(Q-17 is for non-PHC users)

17. Reasons for not using PHC:
a) Not informed (Don't know) about PHC
b) Don't find any reason to use PHC as I am not sick
c) Lack of trust (Don't believe this remote healthcare system)
d) Seems more costly
e) Irregular appearance of PHC
f) I feel more comfortable in conventional system
g) Not interested to try something new
h) Others (……………………………………………………………)

18. Do you agree that ICT base healthcare service (i.e. PHC) can provide healthcare services more quickly than traditional sources?

1	Strongly Disagree	2	Disagree	3	Neutral/Don't know	4	Agree	5	Strongly Agree

19. Using PHC is easier than traditional healthcare services.

1	Strongly Disagree	2	Disagree	3	Neutral/Don't know	4	Agree	5	Strongly Agree

20. Do you think interaction with online doctor is clear and understandable? (Only for existing PHC customers)

1	Strongly Disagree	2	Disagree	3	Neutral/Don't know	4	Agree	5	Strongly Agree

21. Do you think using a new service like PHC is a fun and you would like to try it?

1	Strongly Disagree	2	Disagree	3	Neutral/Don't know	4	Agree	5	Strongly Agree

22. I trust the overall system and technology PHC is using?

1	Strongly Disagree	2	Disagree	3	Neutral/Don't know	4	Agree	5	Strongly Agree

23. The results given by PHC (advice, guideline, prescription) is easily understandable to me.

1	Strongly Disagree	2	Disagree	3	Neutral/Don't know	4	Agree	5	Strongly Agree

24. I am not worried about the data security or privacy issue in PHC.

1	Strongly Disagree	2	Disagree	3	Neutral/Don't know	4	Agree	5	Strongly Agree

25. What is your perception about the cost of PHC services in compare with traditional sources for the same services?

1	Very expensive	2	Expensive	3	No idea / Don't know	4	Equal	5	Cheaper

26. References from others (friends, family, and peer groups) influence me to choose a healthcare service provider.

1	Strongly Disagree	2	Disagree	3	Neutral/Don't know	4	Agree	5	Strongly Agree

27. What is your perception about the overall service quality of PHC?

1	Not good at all	2	Not so good	3	Neutral/Don't know	4	Good	5	Better than traditional

28. I think PHC is overall useful?

1	Strongly Disagree	2	Disagree	3	Neutral/Don't know	4	Agree	5	Strongly Agree

29. I think PHC is overall reliable.

1	Strongly Disagree	2	Disagree	3	Neutral/Don't know	4	Agree	5	Strongly Agree

30. I will use PHC in future.

1	Strongly Disagree	2	Disagree	3	Neutral/Don't know	4	Agree	5	Strongly Agree

Appendix 2: Calculation for Acceptance Behavior (eHealth Acceptance Model)

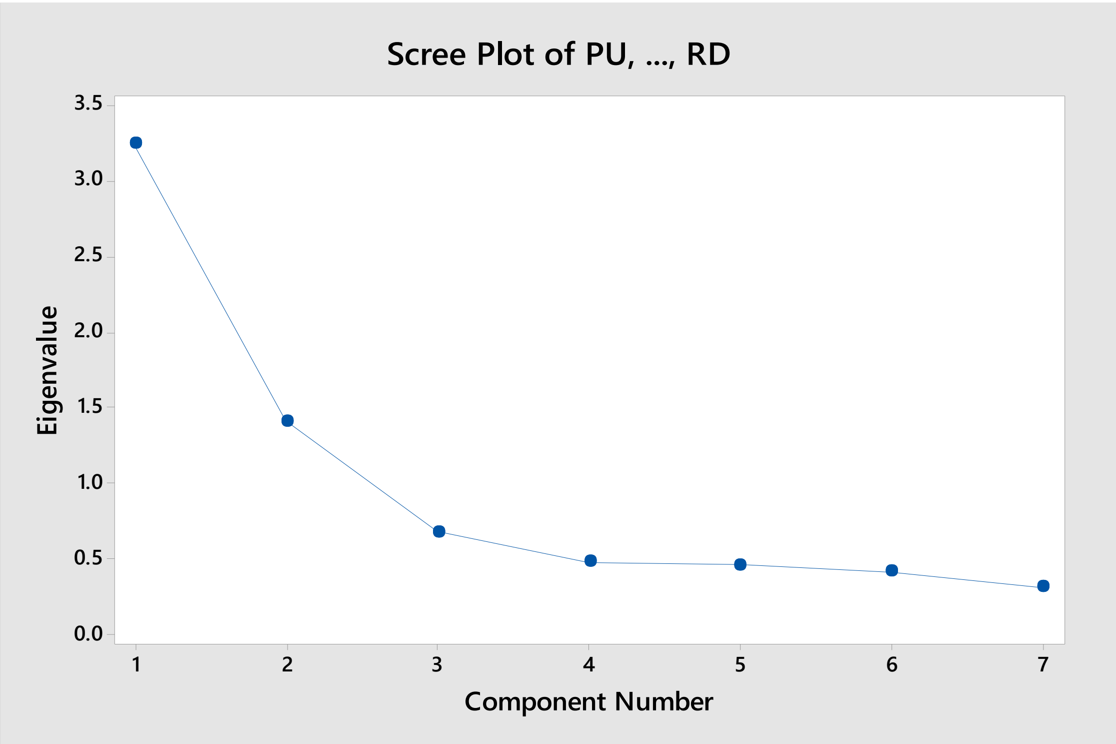
Principal Component Analysis: PU, PEU, PP, PC, SDT, SQ, RD

Eigenanalysis of the Correlation Matrix

Eigenvalue	3.2468	1.4123	0.6787	0.4762	0.4592	0.4174	0.3093
Proportion	0.464	0.202	0.097	0.068	0.066	0.060	0.044
Cumulative	0.464	0.666	0.763	0.831	0.896	0.956	1.000

Eigenvectors

Variable	PC1	PC2	PC3	PC4	PC5	PC6	PC7
PU	0.396	-0.263	-0.478	0.218	-0.468	0.514	-0.123
PEU	0.374	-0.393	0.356	-0.548	0.238	0.188	-0.431
PP	0.366	-0.370	0.501	0.309	-0.367	-0.400	0.298
PC	0.400	-0.248	-0.476	0.103	0.621	-0.293	0.264
SDT	0.371	0.441	-0.228	-0.185	-0.286	-0.558	-0.434
SQ	0.386	0.436	0.085	-0.430	-0.080	0.264	0.626
RD	0.349	0.440	0.329	0.571	0.341	0.272	-0.245



Factor Analysis: PU, PEU, PP, PC, SDT, SQ, RD

Maximum Likelihood Factor Analysis of the Correlation Matrix

Unrotated Factor Loadings and Communalities

Variable	Factor1	Factor2	Communality
PU	0.613	0.316	0.475
PEU	0.586	0.463	0.558
PP	0.558	0.434	0.500
PC	0.619	0.311	0.480
SDT	0.673	-0.367	0.587
SQ	0.726	-0.386	0.676
RD	0.611	-0.321	0.476
Variance	2.7674	0.9859	3.7533
% Var	0.395	0.141	0.536

Rotated Factor Loadings and Communalities

Varimax Rotation

Variable	Factor1	Factor2	Communality
PU	0.646	0.241	0.475
PEU	0.737	0.122	0.558
PP	0.697	0.121	0.500
PC	0.647	0.249	0.480
SDT	0.181	0.745	0.587
SQ	0.203	0.797	0.676
RD	0.173	0.668	0.476
Variance	1.9679	1.7854	3.7533
% Var	0.281	0.255	0.536

Factor Score Coefficients

Variable	Factor1	Factor2
PU	0.246	-0.007
PEU	0.363	-0.084
PP	0.303	-0.068
PC	0.247	-0.004
SDT	-0.054	0.351
SQ	-0.067	0.477
RD	-0.033	0.246

Item Analysis of PU, PEU, PP, PC

Correlation Matrix

	PU	PEU	PP
PEU	0.460		
PP	0.460	0.579	
PC	0.565	0.491	0.427

Cell Contents Pearson correlation

Item and Total Statistics

Variable	Total Count	Mean	StDev
PU	292	3.524	0.913
PEU	292	3.288	0.703
PP	292	3.182	0.656
PC	292	3.815	1.100
Total	292	13.808	2.676

Cronbach’s Alpha

Alpha
0.7803

Omitted Item Statistics

Omitted Variable	Adj. Total Mean	Adj. Total StDev	Item-Adj. Total Corr	Squared Multiple Corr	Cronbach’s Alpha
PU	10.284	2.011	0.6200	0.3897	0.7086

PEU	10.521	2.186	0.6132	0.4192	0.7233
PP	10.627	2.242	0.5787	0.3885	0.7423
PC	9.993	1.854	0.6163	0.3932	0.7319

Item Analysis of SDT, SQ, RD

Correlation Matrix

	SDT	SQ
SQ	0.628	
RD	0.518	0.581

Cell Contents Pearson correlation

Item and Total Statistics

Variable	Total Count	Mean	StDev
SDT	292	3.678	0.833
SQ	292	3.318	0.749
RD	292	3.264	0.675
Total	292	10.260	1.914

Cronbach's Alpha

Alpha
0.7997

Omitted Item Statistics

Omitted Variable	Adj. Total Mean	Adj. Total StDev	Item-Adj. Total Corr	Squared Multiple Corr	Cronbach's Alpha
SDT	6.582	1.267	0.6474	0.4296	0.7321
SQ	6.942	1.316	0.6949	0.4830	0.6729
RD	6.997	1.428	0.6070	0.3761	0.7686

Correlation: Age, Sex, Edu, MEx, ATS, SE, CellPh, Ad, SR

Correlations

	Age	Sex	Edu	MEx	ATS	SE	CellPh	Ad
Sex	0.327							
Edu	-0.315	0.021						
MEx	0.215	0.156	0.324					
ATS	0.216	0.008	-0.107	-0.056				

SE	0.147	0.136	-0.057	-0.042	0.111			
CellPh	-0.239	0.045	0.166	0.093	-0.007	0.029		
Ad	0.140	0.045	-0.026	-0.031	0.164	0.198	-0.029	
SR	0.090	0.117	-0.007	0.014	0.251	0.142	-0.083	-0.018

Cell Contents Pearson correlation

Binary Logistic Regression: Actual System Use versus ... CellPh, Ad, SR

Method

Link function	Logit
Categorical predictor coding	(1, 0)
Rows used	292

Response Information

Variable	Value	Count	
Actual System Use	Yes	171	(Event)
	No	121	
	Total	292	

Deviance Table

Source	DF	Adj Dev	Adj Mean	Chi-Square	P-Value
Regression	14	216.707	15.4791	216.71	0.000
Age	1	9.393	9.3929	9.39	0.002
ATS	1	44.977	44.9771	44.98	0.000
SE	1	13.062	13.0620	13.06	0.000
Sex	1	4.523	4.5233	4.52	0.033
Edu	3	8.780	2.9267	8.78	0.032
MEx	4	5.418	1.3544	5.42	0.247
CellPh	1	6.069	6.0692	6.07	0.014
Ad	1	19.246	19.2459	19.25	0.000
SR	1	33.200	33.1998	33.20	0.000
Error	277	179.487	0.6480		
Total	291	396.194			

Model Summary

Deviance R-Sq	Deviance R-Sq(adj)	AIC
54.70%	51.16%	209.49

Coefficients

Term	Coef	SE Coef	VIF
Constant	-7.20	1.45	
Age	0.0621	0.0210	1.81
ATS	1.518	0.265	1.21
SE	0.744	0.211	1.06
Sex			
M	1.003	0.479	1.32
Edu			
B	2.028	0.822	3.12
C	0.925	0.777	4.02
D	0.638	0.848	4.00
MEx			
B	-0.330	0.655	2.92
C	0.434	0.683	2.63
D	-0.409	0.891	1.92
E	-1.50	1.20	1.60
CellPh			
Yes	1.366	0.569	1.30
Ad			
Yes	1.937	0.468	1.22
SR			
Yes	2.275	0.434	1.31

Odds Ratios for Continuous Predictors

	Odds Ratio	95% CI
Age	1.0641	(1.0212, 1.1088)
ATS	4.5609	(2.7149, 7.6620)

SE	2.1046	(1.3907, 3.1849)

Odds Ratios for Categorical Predictors

Level A	Level B	Odds Ratio	95% CI
Sex			
M	F	2.7271	(1.0658, 6.9776)
Edu			
B	A	7.5995	(1.5170, 38.0706)
C	A	2.5229	(0.5501, 11.5717)
D	A	1.8926	(0.3588, 9.9814)
C	B	0.3320	(0.1137, 0.9697)
D	B	0.2490	(0.0715, 0.8676)
D	C	0.7501	(0.2747, 2.0484)
MEx			
B	A	0.7191	(0.1991, 2.5968)
C	A	1.5436	(0.4049, 5.8842)
D	A	0.6644	(0.1160, 3.8064)
E	A	0.2229	(0.0211, 2.3516)
C	B	2.1465	(0.8211, 5.6117)
D	B	0.9240	(0.2270, 3.7603)
E	B	0.3099	(0.0391, 2.4541)
D	C	0.4304	(0.1036, 1.7878)
E	C	0.1444	(0.0184, 1.1357)
E	D	0.3354	(0.0357, 3.1479)
CellPh			
Yes	No	3.9181	(1.2850, 11.9473)
Ad			
Yes	No	6.9394	(2.7725, 17.3688)
SR			
Yes	No	9.7297	(4.1551, 22.7834)

Odds ratio for level A relative to level B

Regression Equation

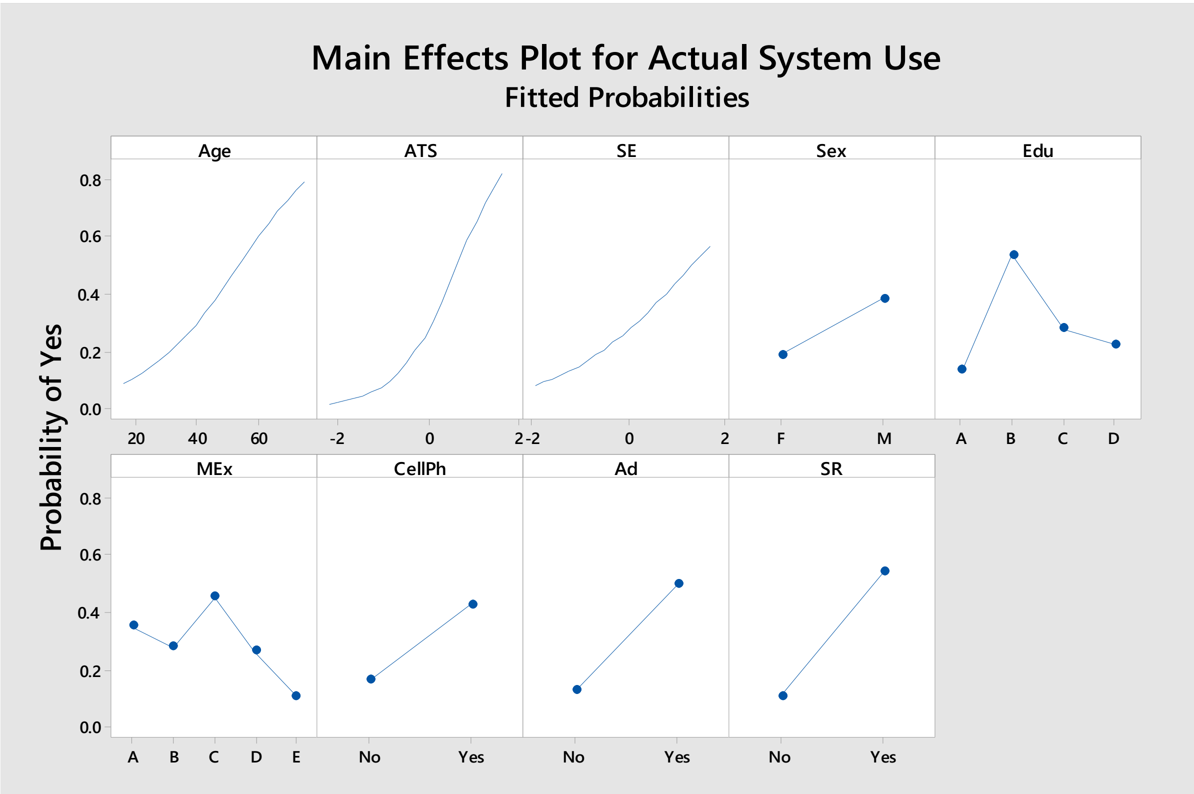
P(Yes) = exp(Y')/(1 + exp(Y'))

Y' = -7.20 + 0.0621 Age + 1.518 ATS + 0.744 SE + 0.0 Sex_F + 1.003 Sex_M + 0.0 Edu_A
+ 2.028 Edu_B + 0.925 Edu_C + 0.638 Edu_D + 0.0 MEx_A - 0.330 MEx_B
+ 0.434 MEx_C
- 0.409 MEx_D - 1.50 MEx_E + 0.0 CellPh_No + 1.366 CellPh_Yes + 0.0 Ad_No
+ 1.937 Ad_Yes
+ 0.0 SR_No + 2.275 SR_Yes

Goodness-of-Fit Tests

Test	DF	Chi-Square	P-Value
Deviance	277	179.49	1.000
Pearson	277	249.37	0.882
Hosmer-Lemeshow	8	6.98	0.539

Factorial Plots for Actual System Use



Appendix 3: Calculation for Compliance Behavior

Binary Logistic Regression: Compliance with ... Use frq, Distance to HF

Method

Link function	Logit
Rows used	95

Response Information

Variable	Value	Count	
Compliance with e-Prescription	1	71	(Event)
	0	24	
	Total	95	

Deviance Table

Source	DF	Adj Dev	Adj Mean	Chi-Square	P-Value
Regression	7	63.850	9.1214	63.85	0.000
Age	1	0.485	0.4846	0.48	0.486
Sex	1	4.596	4.5955	4.60	0.032
Edu	1	4.166	4.1664	4.17	0.041
Mex	1	2.047	2.0473	2.05	0.152
CellPh	1	0.165	0.1647	0.16	0.685
Use frq	1	4.116	4.1161	4.12	0.042
Distance to HF	1	7.576	7.5762	7.58	0.006
Error	87	43.539	0.5005		
Total	94	107.389			

Model Summary

Deviance R-Sq	Deviance R-Sq(adj)	AIC
59.46%	52.94%	59.54

Coefficients

Term	Coef	SE Coef	VIF
Constant	-6.14	2.02	
Age	-0.390	0.569	2.14
Sex	2.017	0.991	1.64
Edu	0.921	0.488	1.11
Mex	1.106	0.811	1.35
CellPh	0.334	0.823	1.62
Use frq	0.994	0.600	1.33
Distance to HF	0.815	0.354	1.34

Odds Ratios for Continuous Predictors

	Odds Ratio	95% CI
Age	0.6769	(0.2219, 2.0651)
Sex	7.5134	(1.0773, 52.3988)
Edu	2.5120	(0.9648, 6.5399)
Mex	3.0225	(0.6165, 14.8196)
CellPh	1.3971	(0.2784, 7.0109)
Use frq	2.7024	(0.8340, 8.7559)
Distance to HF	2.2595	(1.1300, 4.5183)

Regression Equation

P(1) = exp(Y')/(1 + exp(Y'))

Y' = -6.14 - 0.390 Age + 2.017 Sex + 0.921 Edu + 1.106 Mex + 0.334 CellPh + 0.994 Use frq + 0.815 Distance to HF

Goodness-of-Fit Tests

Test	DF	Chi-Square	P-Value
Deviance	87	43.54	1.000
Pearson	87	47.71	1.000
Hosmer-Lemeshow	8	1.54	0.992

Fits and Diagnostics for Unusual Observations

Obs	Observed Probability	Fit	Resid	Std Resid		
35	0.000	0.890	-2.100	-2.21	R	
36	1.000	0.086	2.213	2.28	R	
60	1.000	0.827	0.617	0.71		X
73	0.000	0.399	-1.010	-1.17		X
83	0.000	0.351	-0.929	-1.19		X
86	1.000	0.820	0.629	0.76		X
90	0.000	0.686	-1.521	-1.80		X
91	1.000	0.807	0.656	0.78		X
94	1.000	0.786	0.694	0.81		X

R Large residual
X Unusual X

Appendix 4: Calculation for Predicting Consumer Behavior

Experiment created on: Microsoft Azure Machine Learning Studio (Feb 24, 2018)

Fold Number	Number of examples in fold	Model	Accuracy	Precision	Recall	F-Score	AUC
1	30	Logistic Regression	0.866666667	0.882352941	0.882352941	0.882352941	0.950226244
2	29	Logistic Regression	0.931034483	0.875	1	0.933333333	0.90952381
3	29	Logistic Regression	0.827586207	0.928571429	0.764705882	0.838709677	0.87254902
4	29	Logistic Regression	1	1	1	1	1
5	29	Logistic Regression	0.689655172	0.65	0.866666667	0.742857143	0.723809524
6	29	Logistic Regression	0.827586207	0.866666667	0.8125	0.838709677	0.9375
7	29	Logistic Regression	0.793103448	0.789473684	0.882352941	0.833333333	0.892156863
8	29	Logistic Regression	0.896551724	0.9	0.947368421	0.923076923	0.957894737
9	29	Logistic Regression	0.862068966	0.842105263	0.941176471	0.888888889	0.950980392
10	30	Logistic Regression	0.9	0.909090909	0.952380952	0.930232558	0.952380952
Mean	292	Logistic Regression	0.859425287	0.864326089	0.904950428	0.881149448	0.914702154
Standard Deviation	292	Logistic Regression	0.083812731	0.093266696	0.077554757	0.071562276	0.076311362
Fold Number	**Number of examples in fold**	**Model**	**Accuracy**	**Precision**	**Recall**	**F-Score**	**AUC**
1	30	Decision Tree	0.833333333	0.833333333	0.882352941	0.857142857	0.909502262
2	29	Decision Tree	0.827586207	0.764705882	0.928571429	0.838709677	0.904761905
3	29	Decision Tree	0.75862069	0.857142857	0.705882353	0.774193548	0.867647059
4	29	Decision Tree	0.896551724	1	0.833333333	0.909090909	0.964646465

5	29	Decision Tree	0.75862069	0.7	0.933333333	0.8	0.823809524
6	29	Decision Tree	0.827586207	0.823529412	0.875	0.848484848	0.913461538
7	29	Decision Tree	0.862068966	0.882352941	0.882352941	0.882352941	0.926470588
8	29	Decision Tree	0.931034483	0.947368421	0.947368421	0.947368421	0.973684211
9	29	Decision Tree	0.827586207	0.8	0.941176471	0.864864865	0.950980392
10	30	Decision Tree	0.766666667	0.888888889	0.761904762	0.820512821	0.899470899
Mean	292	Decision Tree	0.828965517	0.849732174	0.869127598	0.854272089	0.913443484
Standard Deviation	292	Decision Tree	0.057623808	0.086822634	0.080815216	0.050940503	0.045027289
Fold Number	**Number of examples in fold**	**Model**	**Accuracy**	**Precision**	**Recall**	**F-Score**	**AUC**
1	30	SVM	0.866666667	0.882352941	0.882352941	0.882352941	0.932126697
2	29	SVM	0.827586207	0.764705882	0.928571429	0.838709677	0.885714286
3	29	SVM	0.689655172	0.75	0.705882353	0.727272727	0.789215686
4	29	SVM	0.896551724	1	0.833333333	0.909090909	0.97979798
5	29	SVM	0.724137931	0.684210526	0.866666667	0.764705882	0.70952381
6	29	SVM	0.75862069	0.736842105	0.875	0.8	0.913461538
7	29	SVM	0.827586207	0.875	0.823529412	0.848484848	0.867647059
8	29	SVM	0.75862069	0.8	0.842105263	0.820512821	0.821052632
9	29	SVM	0.827586207	0.833333333	0.882352941	0.857142857	0.911764706
10	30	SVM	0.866666667	0.904761905	0.904761905	0.904761905	0.936507937
Mean	292	SVM	0.804367816	0.823120669	0.854455624	0.835303457	0.874681233
Standard Deviation	292	SVM	0.068035017	0.094451232	0.061265094	0.0589395	0.080746323
Fold Number	**Number of examples in fold**	**Model**	**Accuracy**	**Precision**	**Recall**	**F-Score**	**AUC**
1	30	Neural Network	0.9	0.888888889	0.941176471	0.914285714	0.959276018
2	29	Neural Network	0.862068966	0.8125	0.928571429	0.866666667	0.90952381
3	29	Neural Network	0.75862069	0.8125	0.764705882	0.787878788	0.87254902

4	29	Neural Network	0.965517241	0.947368421	1	0.972972973	0.994949495
5	29	Neural Network	0.689655172	0.65	0.866666667	0.742857143	0.752380952
6	29	Neural Network	0.862068966	0.833333333	0.9375	0.882352941	0.923076923
7	29	Neural Network	0.793103448	0.823529412	0.823529412	0.823529412	0.867647059
8	29	Neural Network	0.862068966	0.857142857	0.947368421	0.9	0.931578947
9	29	Neural Network	0.827586207	0.833333333	0.882352941	0.857142857	0.931372549
10	30	Neural Network	0.9	0.909090909	0.952380952	0.930232558	0.931216931
Mean	292	Neural Network	0.842068966	0.836768715	0.904425217	0.867791905	0.90735717
Standard Deviation	292	Neural Network	0.078847559	0.079480109	0.070146326	0.068671189	0.065961804

List of Publications

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[1] M. N. Hossain, H. Okajima, H. Kitaoka, F. Yokota, and A. Ahmed, “eHealth Consumer Behavior,” in *Behavior Engineering and Applications*, 1st ed., Springer International Publishing, 2018. ISBN-13: 978-3319764290