Using Mobile Health to Improve Genetic and Heart Diseases Prediction

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ABSTRACT

Introduction: Mobile personal health is a rapidly growing area of health information technology. Mobile personal health users are able to manage their own health data and communicate with doctors in order to improve healthcare quality and efficiency. In recent years, information and communication technologies improvements, along with mobile Internet, offering anywhere and anytime connectivity, play a key role on modern healthcare solutions. Moreover, data on genetic diseases are no exception to this set of data. Therefore, appropriate algorithm and methods of data analysis should be designed.

Methods: The main objective of this research is to investigate the effective factors on more efficiency of medical data. In this article, in addition to analyzing and evaluating the best data mining algorithms used in the medical field, a new combined approach has been provided in order to predict the risk of transmitting genetic diseases. A questionnaire was developed for this task, based on the rigorous study of scientific literature concerning pregnancy and applications available on the market, with 12 data items. The data items contain calendars, genetic diseases and cardiovascular diseases information, health habits, counters, diaries, mobile features, security, backup, configuration and architectural design.

Results: Health telematics is a growing issue that is becoming a major improvement on patient lives, especially in elderly, disabled, and chronically ill. The results of the patients clustering were obtained using the risk of transmitting genetic diseases and according to the criteria of similarity in the ways of transmission as well as using a decision tree to predict whether the individual with the related characteristics has the likelihood to transmit the disease or not. 300 participants were recruited, 92% routinely used and 91% owned a mobile phone. 99% were willing to receive mobile health (m-health) advice, and 79% favored mobile medication reminders. 65.2% would send home recorded information on their blood pressure, weight, medication use and lifestyle to a doctor. 81.9% trusted the confidentiality of m-health data, while 77.1% had no concerns about the privacy of their information.

Conclusion: M-health system proposes healthcare delivery anytime and anywhere, overcoming geographical, temporal, and even organizational barriers with low and affordable costs. This study reviewed the state-of-the-art on m-health system and technologies.

Keywords: Mobile Personal Health, Mobile Health, Genetic Disease, Healthcare, Heart Diseases

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Introduction

Health telematics had become a great topic in terms of medical informatics and healthcare. Currently, hospitals and health systems are relying on information and communication technology (ICT) as a means for improving quality, safety, and productivity of health care services. E-Health connects medical informatics, public health, and business through associated technologies, such as the Internet. However, it has suffered from a slow start due to the low priority given by Hospitals and health systems to ICT in the 90s. Nevertheless, the need to produce a standard for hospital information systems was crucial. In 1987, the International Health Level Seven (HL7) organization [1] was founded and, in 1994, it was accredited by the American National Standards Institute (ANSI). Its name is a reference to the seventh layer of the ISO Open Systems Interconnection (OSI) Reference model also known as the application layer. Currently, the HL7 is adopted by ISO as a reference in terms of international standardization, publishing together several frameworks and related standards for exchange, integration, sharing, and retrieval of electronic health records (EHRs). In the beginning of the new century, between 1999 and 2002, e-Health services have finally awakened and rapidly increased. This growth was analog to the rapid evolution of ICT infrastructures and access to patient data. The Web 2.0 concept and the emerging Web 3.0 have offered healthcare professionals conditions that had never been given before [2]. They also enabled a key element in healthcare systems, the emergence of EHRs or Personal Health Records (PHRs). Usually, healthcare providers keep and handle patient health records. However, it is becoming more common that patients also request access to those data. Medical records (or health records) allow medical doctors to easily access patient information without the need to ask them in person. E-health systems are typically sustained on EHRs [3]. An EHR-system is basically a repository of information regarding the health records of patient/consumer in a computer form [4]. The deployment of a public EHR-system can offer several advantages to a public healthcare system, for instance, lower and more efficient management costs, more efficient management of high-volume patient data, and centralized medical patient records [5]. M-Health systems and its corresponding mobility functionalities have a strong impact on typical healthcare monitoring and alerting systems, clinical and administrative data collection, record maintenance, healthcare delivery programs, medical information awareness, detection and prevention systems, drug-counterfeiting, and theft [6]. Typical m-Health services architectures (presented in Figure 1) use the Internet and Web services to provide an authentic pervasive interaction among doctors and patients. A physician or a patient can easily access the same medical record anytime and anywhere through his/her personal computer, tablet, or smartphone. The patient can contact the physician in case of an emergency, or even, have access to medical registers or appointments regardless of time and place. In addition, the medical field is expanding and evolving every day and constantly producing large amounts of data [7, 8]. Medical data are produced in more different ways than in the past [3]. The need for an efficient and accurate solution for new managements makes more sense than ever before [9].

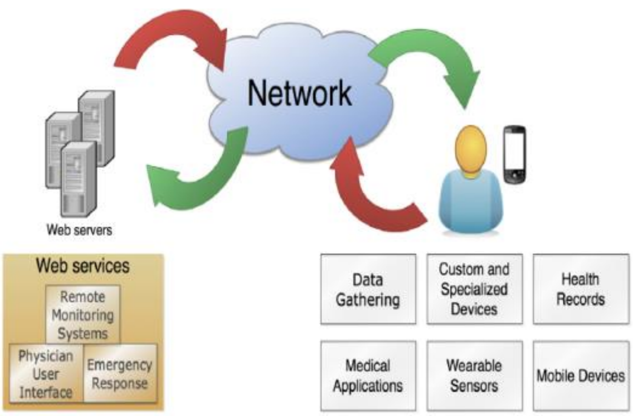

Figure 1. A typical framework of m-health services.

In this regard, there is need for methods and automated algorithms to operate this volume of data with different forms so that we can analyze the data, and then perform operations on them to achieve the desired results [10, 11]. Therefore, smart and flexible methods and data mining algorithms, which are appropriate to the data and their changes, are required [12] and genetic data are not exempted from these data. With regard to genetic data, there is also need for an approach that in addition to reviewing the data, analyze them as well [13]. One of the major problems for choosing this approach is that providing genetic data for each patient may require the need to save characteristics that are not needed for other patients; for example, there may be the need to save a patient's blood test results but for other patients, it is not a priority to do this test and save its results or we may encounter cases that were initially not foreseen while examining the patient's condition. For this reason, it is better not to design a general plan for the database from the beginning so that we can have the possibility of adding any characteristic that is needed during the operation. Another important issue is that considering the need for genetic data of family members and the previous generations, it must be possible to add new attributes (previous and next generations) while performing researches in this database [14]. Genetic diseases are one of the main causes of failure in the world and early diagnosis and prevention is the best treatment. Data mining can be effectively used for the fast and cost-effective prediction and diagnosis of diseases [15]. In this regard, considering the volume and format of data for the study of transmission of genetic disorders and importance of studying the relationship between individuals in this type of disease, it is important that each patient may require specific data that exist, thus it is not possible to define the predetermined schema. With regard to genetic diseases, data that are required to be saved are varied. Considering the nature of genetic disease, there is also the need to save health status of patients' ancestors to understand the transmission of these diseases and new person may be added to the family tree in each investigation. Also, it is very important to explore the transmission route and the relationships between individuals in this database [1, 16, 17]. Thus far, few models have been used to analyze medical data but each of these data model has a number of disadvantages which make them to be non-ideal data model. One of these data model is the relational data model. The next model is the object-relational data models, which solve the predefined schema problem and well define different data formats using Entity attribute value (EAV) design, but still remains the problem of relationships between individuals [18]. The main objective of this article is to use data mining techniques for data clustering by K-means algorithm and combine it with the decision tree in order to predict the risk of transmitting genetic diseases.

Given the importance of our topic, in this study, we examined those dimensions which are able to represent an observable plan of mobile health. Hence, mobile health is examined from the four dimensions, as shown briefly in Figure 2.

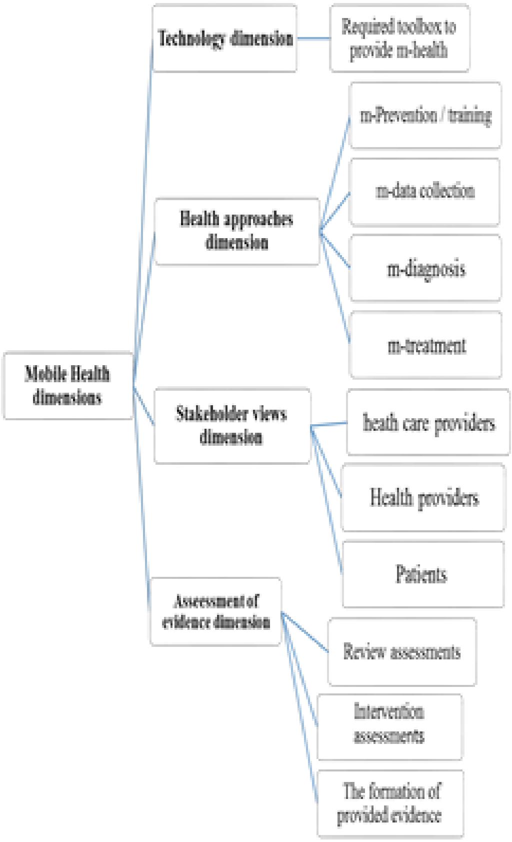

Figure 2. A view of mobile health dimensions

The current evidence suggests growing effectiveness of mobile health programs to encourage a wide range of health behavioral changes. Nevertheless, there are considerably few studies to help designers of interventions to consciously make choice of tools and technology devices, with the aim of involving participants and help them to achieve significant therapeutic results. In the case of mobile health interventions, specific forms of access to the operating system of mobile devices and application are very important. Two basic tools for providing mobile health interventions- text messaging and IVR or interactive voice response- were available in early mobile phones. However, while designing health intervention required tools on the smart-phones, text messaging and IVR were still persisted with the difference that they were much more versatile and powerful. Designing different applications that run solely on smart-phones, made providing of health services on the smart-phones possible. One of the advantages of the smart-phones is access to the Internet, which in turn provides the access to web-based content, using GPS to track the location, providing online travel guide with online maps, and broadcasting of audio or video content. In the following, tools that can be used in smart-phones to provide mobile health will be mentioned, respectively.

The information management systems health Appscore [19] was used to define which the best applications are based on functionality, patient reviews, and their potential to lower the cost of care services. The top m-health applications in each therapy areas are presented in Table 1.

Table 1. The m-health applications by therapy area

Reference	Area	Description

(20)	Prevention/Healthy Lifestyles	Diet application for calories counting, food tracking, exercise, and weight goals. Furthermore, it explores social aspects including links to friends as a motivation feature.
(21)	Prevention/Healthy Lifestyles	Diet application for calorie counting, food tracking, And exercise using weight goals as a motivation aspect.
(22)	Prevention/Healthy Lifestyles	Weight training and fitness application with intents And claims to replace a personal trainer.
(23)	Finding a healthcare professional/facility	An application that allows patients to communicate with their physician's office and also have access to up-to-date health records. Furthermore, it serves as an appointment reminder. also includes visit summaries and
(24)	Finding a healthcare professional/facility	This application provides a lists of local doctors rated By previous patients that have also use this App. The search can be performed through symptom, condition, or medical specialty.
(25)	Finding a healthcare professional/facility	An application that uses zip code searches to find and Book doctors' appointments.
(26)	Diagnosis/Education	An application that contains health answers and healthy Tips on any symptom, condition, medication, health concern, or even wellness topics From 47,000 U.S. medical doctors.
(27)	Diagnosis/Education	An application that contains information of several Medical symptoms, diseases, conditions, procedures, medications, and drugs.
(28)	Diagnosis/Education	An application that contains information of several medical symptoms, diseases, conditions, procedures, medications, and drugs. It includes WebMD's Symptom Checker.
(29)	Filling Prescription	This application compares and provides prices for Prescription drugs. Furthermore, it also provides coupons and savings tips for more than 6,000 U.S. drugs in several pharmacies in the
(30)	Filling Prescription	This application allows to order medications and get them delivered to a defined location. Moreover, it includes also medication and appointment reminder.
(31)	Filling Prescription	An application that features medication prescriptions refill by scan function, points for refills, pill reminders, transfer prescription feature and Health references encyclopedia.
(32)	Compliance	A medication reminder featuring a large drug database and the ability to support Multiple users.
(33)	Compliance	A prescription reminder that features prescription alarms, reminder scheduling, setup reminders, and medication intake tracking.
(34)	Compliance	A prescription reminder that features prescription alarms, reminder scheduling, setup reminders, and medication intake tracking.
(35)	Diabetes	An application that tracks daily nutrition intake of food, carbs, fiber, fat, tracks quantity of water intake, readings of glucose, HbA1c, blood pressure, heart rate, weight, exercise, medications, and insulin.

The health IT Usability Evaluation Model (Figure 3) was developed in response to the current gaps in the existing usability models which had previously been developed [17].

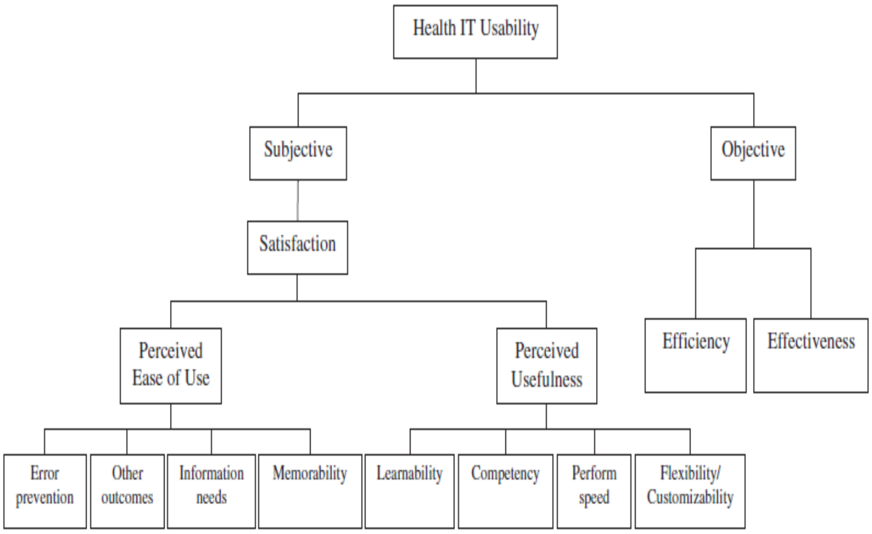

Figure 3. Health information technology usability evaluation model.

Today, large volumes of medical data are generated in various forms. Efficient analysis and use of this data in a reasonable time requires appropriate data mining approaches. Xu et al, 2015, conducted a survey research on data mining approaches used to predict heart diseases [(6)]. They stated that data mining is the process of finding useful and relevant information from the database. There are several types of data mining techniques. Association rules, classification, neural networks, clustering are among the most important data mining methods. Data mining process plays an important role in industry and health service. The data mining processes are widely used in the healthcare field to predict diseases. In their paper, they analyze different types of processes to predict heart diseases using data mining [(12)]. Daraei et al., 2015, investigated and analyzed the use of association classifiers in the predictive analysis in data mining in the field of health and medical services [(7)]. Association rule mining is one of the most important data mining techniques for anatomical tasks and a lot of research has been conducted in this area and was used for the analysis of tool basket. Classification using association rules is another primary predictive analysis method, which aims to discover small set of rules in the mass of data of databases that are considered an accurate classifier. They expressed that they have offered a combined approach that combines association rule mining with classification rules mining and call it association classification (AC). This is a new classification approach. This integration was carried out with a focus on mining a particular subset of association rules that are called classification association rules (CARs) and classification is carried out by these CARs. The use of association rules mining for classification systems is a promising approach. Considering their legibility, association classifiers are very useful and convenient for experts in the decision-making process. The medical world is a good example of such application. Consider a situation, in which a physician wants to examine a patient. There is vast amount of information about the patient's condition (including personal data, test results, etc.). A classification system can help the physician in this work. The system can assess whether the patient is at risk of certain diseases in the future or is incompatible with some treatments. Given the output of the classification model, the physician can make a better decision regarding the patient treatment. Combining advanced classification rules mining with classifiers provides a new type of association classifiers. They discussed that this advanced association classifiers, which have been proposed in recent years, are more accurate than traditional classifiers [(13)]. Stork et al., in a study, investigated the use of decision tree to diagnose the heart disease of patients. They stated that the heart disease is the leading cause of death in the last 10 years. The researchers used several data mining techniques in order to help healthcare professionals diagnose heart diseases. The decision tree is one of data mining methods that have been successfully used in recent years. Nonetheless, most researches have used the J 4.8 decision tree based on interest rates and binary discretization. Gini index and information gain are two other successful decision trees that have been less used in the diagnosis of heart disease. In addition, other discretization techniques, voting method, and reduced error pruning were known as better decision trees. This research investigates the application of some techniques in different types of decision trees to obtain better performance in the diagnosis of disease. Bench-marking databases that are widely used were employed in the research. To evaluate the performance of alternative decision trees, sensitivity, specificity and accuracy were calculated. This research proposes a model, in which J 4.8 decision tree and bag algorithm has a better performance in the diagnosis of heart disease [14]. Millar et al. evaluated the association rules and decision trees to predict the multifunctional properties. They stated that the association rules and decision trees and data mining techniques are well-known in finding predictive rules. In this study, they provided a detailed comparison on the association rules and decision tree so that the multifunctional properties are predicted and the important differences between the above two techniques for such purpose are identified. They conducted an extensive test on the actual medical databases so that the data mining process is conducted on rules that predict a disease in several coronary arteries. The prerequisite for the association rules contains medical measurements and risk factors, while its consequences are degree of severity of the disease in one or more arteries. Predictive rules by the association rules mining are more frequent and enjoy higher reliability than the predictive rules induced by the decision tree [15-17]. The purpose of this paper is to analyze the features and functionalities of mobile PHRs focused on genetic diseases and cardiovascular diseases monitoring, in order to discover whether or not they comply with the needs, guidelines and scientific pregnancy literature with regard to tracking pregnancy. The rest of the paper is organized as follows: The second section presents the literature review of the research. The three sections provide the theoretical method. In the fourth section, the results are explained. In the fifth section, the discussion and conclusion are provided.

Methods

We used two exemplars to assess the appropriateness of the health information technology usability evaluation Model for evaluating the usability of m-Health technology. In the first exemplar, we conducted 6 focus group sessions to explore adolescents' use of mobile technology for meeting their health Information needs. The main objective of this research is to investigate the effective factors on more efficiency of medical data. In this article, in addition to analyzing and evaluating the algorithms used in the medical field, a new combined approach has been provided in order to predict the risk of transmitting genetic diseases. A questionnaire was developed for this task, based on the rigorous study of scientific literature concerning pregnancy and applications available on the market, with 9 data items and 35 quality assessments. The data items contain calendars, genetic diseases and cardiovascular diseases information, health habits, counters, diaries, mobile features, security, backup, configuration and architectural design. In this article, a collection of genetic data is used. There are many symptoms of genetic disease, finding patterns of the genetic disease data are helpful in diagnosing the cause of the disease and its transmission in the future. Database used in this article consists of 303 samples, including 297 full samples and six samples with lost values. This database has 76 raw attributes while all trials were performed only on 5 of their attributes. Therefore, this database contains 3 symptoms of the genetic disease transmission and the meaning of each of the symptoms will be described later (Table 2). A questionnaire regarding mobile phone usage and possible use in healthcare was verbally administered in five primary health centers. People, with access to a mobile phone were recruited by convenience sampling in partnership with accredited social health activists. Quantitative data analysis was conducted using SPSS software.

Table 2. Database components for m-health

Component	Label	Attribute
Patient's age	Age	Age
Patient's gender	Sex	Sex
Single-gene disease	SGD	Single-gene diseases
Multi-genic disease	MGD	Multi-genic diseases
Mitochondrial diseases	Mt-DNA	Mitochondrial diseases

Genetic diseases are divided into 3 categories: monogenic diseases, multi-genic or multi-factor diseases, mitochondrial diseases. Monogenic diseases are diseases that are transmitted from patient's parents or carriers to children who suffer from the disease at birth, but their age of onset is different in the body, such as thalassemia. These diseases are divided into two dominant and recessive categories, which are described below. Multi-genic diseases are diseases, in which genes suffer from problems caused by environmental changes and disease occur in the body, such as cancers, in development of which eating and lifestyle habits such as smoking play an important role. Mitochondrial diseases are diseases that are transmitted only from mother to child and not the father. There are two modes of transmission with regard to the monogenic diseases: recessive disease, dominant disease. Parents are not ill in the recessive disease and have no symptoms. But their child may be infected with the disease from past generations. In fact, parents are only carriers of disease and are not ill in this type of disease, which includes albinism, skin cancers, cystic fibrosis, mental retardation, sickle cell anemia, phenylketonuria, thalassemia, etc. Mother of father or both suffer from the genetic disease and their children are very likely to be ill in the dominant disease such as dwarfism, multiple skeletal abnormalities, cataracts, muscle weakness and dystrophy, syndactyly, short toes with hands and feet disorders, psoriasis, Huntington's, cancer, eye retinas etc. Other types of genetic diseases include hemophilia, Duchene muscular dystrophy (DMD), different types of deafness, cleft lip and cleft palate, mental illness, rickets resistant to vitamin D, favism, insipidus diabetes, color blindness etc (gender-dependent diseases). A K-means algorithm is used in the first stage of data clustering process. It also increases the accuracy and speed of data processing. The proposed methodology that consists of different sections, the genetic database, includes a number of attributes, which are used to distinguish the risk of transmitting a genetic disease from the lack of transmission. As previously mentioned, the database contains 5 columns and 303 rows. Four [4] columns represent the attributes and 1 column represents the class label. The next step is to create a decision tree, through which the database components are weighted. A weighted mean is achieved for each person. Based on association rules, any person whose weighted mean is higher and less than 50% is at risk of disease transmission and safe, respectively. Figure 4 shows the step by step production of the decision tree.

In addition to having a simple and tangible structure and high accuracy, decision tree has an important attribute such as its feature selection. This means it specifies, among different entries, the entries that have more weight in the classification and are known as dominant feature. For example in the following decision tree, among the various features used in the input, only four features, including single-gene diseases, multi-genic diseases, mitochondrial diseases and triggers of disease have been marked as dominant features affecting the classification. This property of the decision tree can be used in problems, the feature space of which is very large. Initially, the dominant features are selected using the decision tree and then the dominant features can be used as input of any custom expert system. It can improve the performance of the expert system.

Results

Among the 300 individuals approached, 276 were willing to participate, 14 were ineligible due to lack of access to a mobile phone. Two hundred and sixty two (262) successfully completed the questionnaire. Socio-demographic characteristics of eligible participants are detailed in Table 3. Ownership: 231 (88.2%) individuals owned a mobile phone. Male sex (OR = 7.64; 95% CI = 1.89–30.98; p = 0.004), completion of high school education (OR = 11.49; 95% CI = 2.49–53.15; p = 0.002) and a higher education qualification (OR = 7.14; 95% CI = 1.16–43.94; p = 0.03) were associated with mobile ownership. Among mobile phone users, 204 (83%) were in sole possession, the remainder sharing with a family member. Twenty three (54.8%) shared with a spouse, 12 (28.6%) shared with their entire family, 4 (9.5%) shared with a son or daughter, 3 (7.1%) with a sibling. Unskilled or semi-skilled employment (OR = 6.35; 95% CI = 1.85–21.87; p = 0.003), and a higher education qualification (OR = 7.68; 95% CI = 2.32–25.44; p = 0.001) were associated with sole ownership.

Mobile phone use

SPSS version 20 was used for data analysis. Kolmogorov– Smirnov tests were used to identify variable normality. Relevant variables with statistical significance of $p < 0.10$ were identified using Chi-square tests for categorical covariates, Kruskal Wallis for non-continuously distributed covariates and independent sample t-tests for continuously distributed covariates. Logistic regression was used to investigate the relationship between these variables and mobile phone usage characteristics. A p-value 0.05 was considered statistically significant. Two hundred and twenty eight (87%) participants reported routine use of mobile phones. Of those not routinely using mobile phone, 10 (34%) stated preferential use of landline connection, 6 (21%) cited financial constraints, 6 (21%) cited inability to use a mobile phone, 6 (21%) stated they had no use for mobiles, while 1 (3%) stated that a family member used a mobile phone on their behalf. Male sex (OR = 6.84; 95% CI = 1.92– 24.41; p = 0.003), completion of high school (OR = 9.55; 95% CI = 2.41–37.81; p = 0.001) and a higher education qualification (OR = 7.39; 95% CI = 1.36–40.32; p = 0.021) were associated with routine use. Participants made 3 (median) outgoing calls per day, and received 4 calls (median). Two hundred and twenty (84.3%) used SMS (_1 SMS per week). Participants sent 2.16 SMS daily (mean), and received 4.49 SMS (mean). Decreasing age (OR = 0.95; 95% CI = 0.92–0.99; p = 0.009) and un-skilled or semi-skilled occupation (OR = 3.26; 95% CI = 1.05–10.16; p = 0.04) were associated with SMS usage. One hundred and fifty four (58.8%) used the alarm function on their mobile phones: 149 (89.8%) to wake up, 16 (9.6%) as a reminder of errands, and only 1 (0.6%) as a medication reminder. One hundred and nine (41.6%) used their mobile phone for other purposes: 89 (37.9%) to listen to music/radio, 68 (28.9%) to take pictures, 51 (21.7%) to browse internet or social media, 25 (10.6%) to play games and 2 (0.8%) to use communication applications (e.g. WhatsApp).

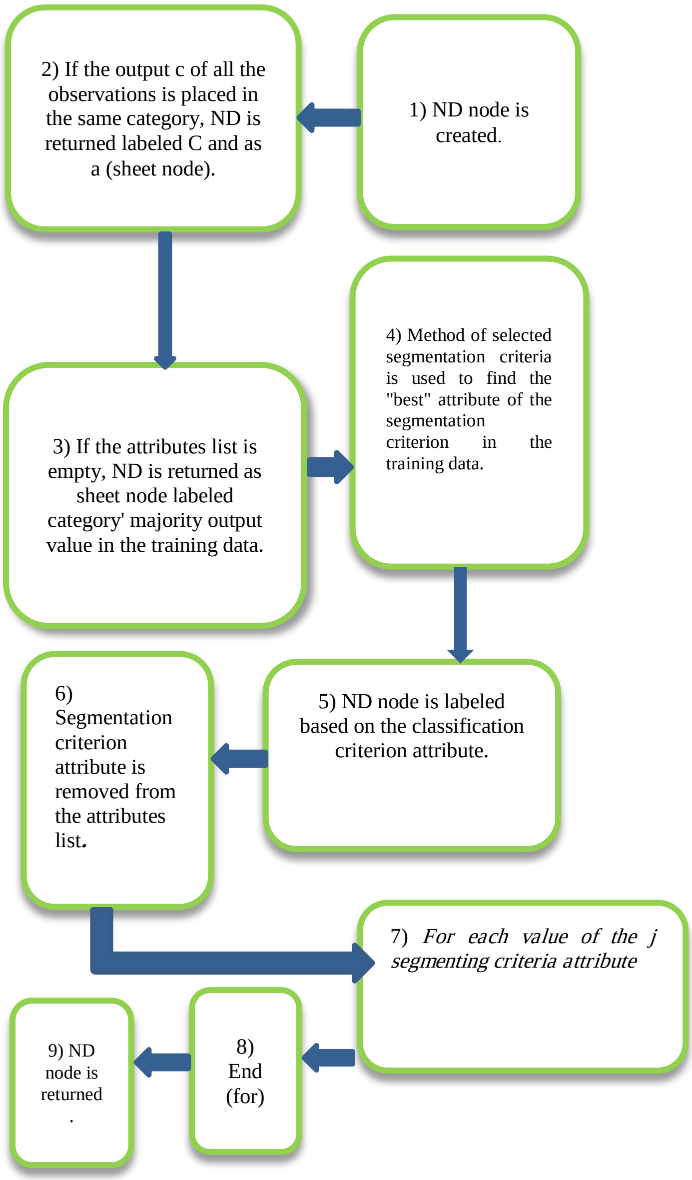

Figure 4. The production process for m-health service

Decreasing age (OR = 0.89; 95% CI = 0.86–0.92; $p < 0.001$), male sex (OR = 3.51; 95% CI = 1.47–8.41; p = 0.005) and a higher education qualification (OR = 7.45; 95% CI = 1.25–44.27; p = 0.03) were associated with other usage, excluding SMS and alarm functions.

Figure 5 depicts health topics on which participants would receive information and advice. Requesting information on exercise and physical activity were associated with mobile ownership (OR = 4.77; 95% CI = 1.34–17.04; p = 0.02) and absence of diabetes diagnosis (OR = 0.29; 95% CI = 0.13–0.69; p = 0.005). Request for advice on weight loss was associated with mobile ownership (OR = 4.23; 95% CI = 1.18–15.17; p = 0.03) and absence of diabetes diagnosis (OR = 0.28; 95% CI = 0.12–0.65; p = 0.003).

Table 3. Demographic profile of respondents and audiences' characters

Characters	Frequency	Percent (%)	
Gender	Female	67	22.33
	Male	233	77.67
Age	18-20	32	10.67
	20-23	113	37.67
	23-25	81	27
	25-28	65	21.67
	>28	9	3
Marital status	Single	146	48.67
	Married	154	51.33
Education level	Associate	20	6.67
	Undergraduate student	135	45.00
	Master of Science student	89	29.67
	MPhil student	8	2.67
	Ph.D student	48	16.00
Do you have mobile phone?	<1 years	29	8.6
	1-3	103	34.6
	3-5	118	40.8
	5-7	36	11.5
	>7 years	14	4.5
Do yoy have mobile phone?	Yes	263	91
	No	27	9
Time to use mobile phone?	Less than 1 year	96	32
	1-2 years	130	43.33
	2-3 years	57	19
	More than 3 years	17	5.66
Internet usage	<1 hours	36	12
	1-2 hours	79	26.33
	2-3 hours	117	39
	3-6 hours	52	17.33
	>6 hours	16	5.34
Diagnosis of NCD	Male	Female	p-value
Any	(48.3) 58	(53.9) 76	0.423
HTN	(26.1) 31	(26.4) 37	0.945
High cholesterol	(10.1) 12	(14.3) 20	0.306
CVD	3 (2.5)	3 (2.1)	0.840
DMII	22 (18.3)	26 (18.6)	0.986
COPD	2 (1.7)	2 (1.4)	0.870
Cancer	(0.8) 1	(0) 0	0.277
Medications			
Any	(40.8) 49	(39.7) 56	0.854
HTN	(25.8) 31	(25.7) 36	0.983
Statins	(10) 12	(12.1) 17	0.584
DMII medications	(15.8) 19	(12.9) 18	0.493
Insulin	(1.7) 2	(0.7) 1	0.473

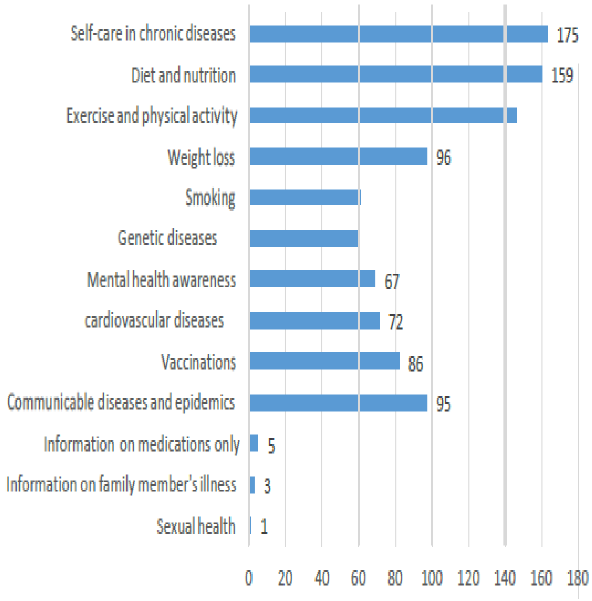

Figure 5. Area of mobile health.

This method has been implemented by using the database and combining clustering algorithm and decision tree in MATLAB. The weight matrix that has been created for each person by weighting the decision tree based on the description of each of the components, is a 5 × 303 matrix and some part of it is given in Tables 4, 5 and 6 in database due to its high volume.

Table 4. Sample weight matrix

Individuals	Gender	Age	Monogenic	Multi-genic	Mitochondrial disease
First person	0	0.103	0	0.132	2.883
second person	0	0.155	1	0.25	3.766
Third person	0	0	0.8	0.015	3.166
Fourth person	0	0	0.9	0.015	2.4
Fifth person	0	0.012	0.9	0	2.933

Now, the weighted mean matrix, which is 303 × 1 matrix is achieved for each individual. Part of the above matrix is shown here due to lack of space (Table 5).

Table 5. Sample weighted mean matrix

Criteria / algorithms	Accuracy	Specificity	Sensitivity	Negative predictive value	Positive predictive value
Genetic Algorithm	0.76	0.80	0.74	0.71	0.82
Neural network	0.85.7	0.88	0.83	0.82	0.88
Support Vector Machine	0.85.7	0.93.3	0.80.8	0.78.3	0.93
Proposed method	0.86.5	0.88.8	86.04	0.85.1	88.09

Individuals at risk can be identified using this weighted mean matrix using a decision tree. It's like this:

If the weighted mean is above 50%, the individual has high probability of transmission of the genetic disease.

If the weighted mean is below 50%, the individual is not at risk of transmission of the genetic disease.

Different criteria are used to compare the results of the implementation of the proposed method and 4 other most commonly used algorithms:

1. Accuracy: Number of samples correctly diagnosed in the intended class compared with the whole samples.

2. Sensitivity: Number of samples that have correctly shown the absence of disease transmission compared to the total number of samples that have really not shown the genetic disease.

3. Specificity: Number of samples that have correctly shown the presence of disease transmission compared to the total number of samples that really suffered from the genetic disease.

4. The positive predictive value: Number of samples that have correctly shown the absence of disease compared to the total number of samples that are not suffering from the predicted disease.

5. The negative predictive value: Number of samples that have correctly shown the presence of the disease compared to the total number of samples that are suffering from the predicted disease.

Based on the previous assessments and their results, as evident from Table 6, if the proposed methodology is set aside and other common and simple method is compared, the following results are obtained: Vector machine algorithm is in the positive predictive value and superior feature and it has the lowest sensitivity and negative predictive value compared to the percentage of this criterion in genetic algorithm (GA). However, the proposed method has better performance in several criteria than other algorithms. Nevertheless, it is noteworthy that it is in the second place in terms of two criteria, including positive predictive value and specificity, but in general, it is ranked higher than other methods especially based on the accuracy criterion, which partly led to better diagnosis of the genetic disease transmission.

Table 6. Comparison of different criteria on algorithms based on the percentage

Individuals	First Person	Second person	Third Person	Fourth person	Fifth person
Weighted mean	0.587612	0.610657	0.464119	0.530689	0.49351

Discussion

In this paper, these features are discussed and possible paths for future development of similar applications are proposed, which may lead to a more efficient use of smartphone capabilities. M-health technology is growing exponentially. New wireless technologies and optimized m-health are adding to the ubiquity of mobile device use. Consequently, users are increasingly using m-health technology to meet their health information needs, self-management of their health and as communication tool with their providers. Researchers and interventionists are finding ways to integrate mobile technologies in public health and clinical practice. Thus, it is fundamental to evaluate the usability of m-health technology before interventions are put into practice. A number of challenges occur in the development of m-health technologies. As noted in earlier studies, the length of time required to develop content, complete usability testing and iteratively refine systems is a barrier to development. In addition, there are few usability frameworks, which have been developed or evaluated for m-health technologies, which is an impediment for rigorously evaluating these technologies. Findings from this paper fill a gap in the literature by assessing the use of the m-health technology.

Conclusion

In this paper, these features are discussed and possible paths for future development of similar applications are proposed, which may lead to a more efficient use of smartphone capabilities. The m-health is evidence-based and draws its concepts, constructs, and items from widely used and tested usability frameworks. The aim of this study was to elucidate the usefulness of the m-health for evaluating the usability of technology.

Increasingly growth of data on one hand created a new challenge, but on the other hand, it provides different new opportunities which can open new horizons to the researchers, physicians, businessmen and officials in case of being used and explored correctly. Therefore, based on the importance and nature of the medical records and information, there are activities required such as privacy and confidentiality preservation and defining access levels and supervision which can minimize the risk of sensitive data loss and unauthentic accesses. In this article, the performance of these algorithms is compared for more accurate prediction of disease transmission under the same condition and based on a series of measures such as the positive predictive value, negative predictive value, accuracy, sensitivity and specificity. The results show that support vector machine algorithm outperformed the other two simple algorithms and the neural network and genetic algorithms offered better prediction at the end, while the proposed combined approach is developed using different parameters and outperformed the simple methods.

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Conflict of Interest

None declared by authors.

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