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Sevgi Özkan Yildirim · Evren Sumuer
Editors

Current and Emerging mHealth Technologies

Adoption, Implementation, and Use

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ISBN 978-3-319-73134-6 ISBN 978-3-319-73135-3 (eBook)
https://doi.org/10.1007/978-3-319-73135-3

Library of Congress Control Number: 2018935274

Printed on acid-free paper

This Springer imprint is published by the registered company Springer International Publishing AG part of Springer Nature.
The registered company address is: Gewerbestrasse 11, 6330 Cham, Switzerland

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Chapter 1
Introduction to Current and Emerging mHealth Technologies: Adoption, Implementation, and Use

Emre Sezgin

The proliferation of smart mobile devices and increase in Internet access enabled many of the populations to reach many services with minimum efforts. The reports presented that the economic impact of the mobile market is estimated to reach to 14-digit numbers and over 100% annual growth rate. Mobile devices provide accessibility, reachability, and availability regarding exchanging information. In this context, mobile health (mHealth) is an important factor as a major component of electronic health services.

1.1 Mobile Health

Today, mobile health can be considered as an umbrella term for mobile information communication and network technologies accessing to the systems and services of healthcare (Adibi 2015). It includes the mobile devices and peripherals which are used by healthcare providers, patients, and customers in order to gather, store, and analyze data in the decision-making process. It was reported that health services adopted the mobile technologies and promoted its use by the healthcare professionals (Deloitte 2013; WKH 2013). Thus, there were a number of mobile healthcare services in particular use for diagnostic stages and health management, such as smartphone applications, emergency services, echography, and telemedicine applications (Istepanian et al. 2010; Hussain et al. 2015). Similarly, there were studies in the literature about the use of mobile devices and applications in healthcare services (Istepanian et al. 2010; Hampton 2012).

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E. Sezgin et al. (eds.), *Current and Emerging mHealth Technologies*,
https://doi.org/10.1007/978-3-319-73135-3_1

However, in the light of these developments, there has been a puzzle that the mobile healthcare services might not have reached the expected level of quality (Visvanathan et al. 2011; Munos et al. 2016). By the growth of the market, security, regulations, transformation, costs, and technology use were identified as key issues which affect the quality of service and effective dissemination of mobile health. For instance, increasing use of mobile communication technologies may reveal multifaceted risk issues, such as electromagnetic risks, patient security risk, confidentiality and data security risk, and distraction and safety issues (Visvanathan et al. 2011).

It is a fact that mobile health significantly reduces the cost and increases the accessibility, yet the use of the technology may also depend on many other factors that cannot be easily quantified. In this context, a sociotechnical perspective stands as an important indicator toward understanding the use of the technology by the end users. For the success of the technologies, it is critical to develop an understanding about existing mobile health opportunities and what influences on the users' decisions to use these technologies. Otherwise, lack of sociotechnical knowledge may impede the potential success of the technologies. The adoption decision of users (i.e., patients, healthcare providers) may show changes over the time considering the change in technologies and culture. Thus, there is no golden standard to assess user intentions, but a continuous investigation is required to understand the mobile health technologies as well as the influencing factors to use these technologies.

1.2 Our Contribution

Regarding the sociotechnical perspective in mobile health, we believe it is significant to report the knowledge on the implementation, adoption, and use of mobile health technologies. In this book, authors mirrored the current state of mobile health from a sociotechnical perspective in four parts, which are "Behavioral Change," "Monitoring and Tracking with mHealth," "Use and Adoption in Healthcare Delivery," and "Global Perspectives and Issues." The first part, "Behavioral Change in mHealth," covered three chapters about persuasion strategies, technologies, and behavioral change techniques. The second part, "Monitoring and Tracking with mHealth," has four chapters reporting mHealth use in tracking during pregnancy, physical activity, weight loss, and emergency services. The third part is "mHealth Use and Adoption in Healthcare Delivery." This part has five chapters about usability of mHealth, physicians' mHealth app use trends and their adoption, and mobile patient assistance technology in healthcare delivery. The last part, "Global Perspectives and Issues with mHealth," included four chapters. In this part, mobile access to healthcare in Africa, big data use in mHealth, use of sensors, and IoT in mobile health were outlined.

In the second chapter, "Use of Persuasion Strategies in Mobile Health Applications," Nurcan Alkış and Duygu Fındık-Coşkunçay conducted a literature review. Their chapter reported suggestions and implications for behavior change theories and persuasion strategies that were used for mobile health applications. These theories included elaboration likelihood model, social cognitive theory, theory of planned behavior, cognitive behavioral therapy, transtheoretical model of behavioral change, Cialdini's six principles of persuasion, and Fogg's behavior model. The chapter also summarized how these applications were used to change health-related behaviors.

The third chapter, "Behavior Change Techniques Used in Mobile Applications Targeting Physical Activity: A Systematic Review" by Hakan Kuru, presented an overview of behavioral change techniques used in physical activity applications. The author reported a taxonomy including 26 different behavior change techniques and 7 different health behavior theories. The chapter summarized that providing feedback on performance, prompting specific goal setting, and providing instructions for users are the most frequently used behavior change technique.

In the fourth chapter, "Exploring Intention on Continuous Use of Mobile Health Applications Designed by Persuasive Technology: 'Adımsayar' Case Study" by Seray Öney Doğanyiğit, an integrated research model based on theory of planned behavior and Fogg's captology was used to understand the intention to use a mobile app. The name of the app is "Adimsayar," which is a health tracking and motivation application designed by persuasive technology techniques. The data for the study was collected from over 200 participants and analyzed using multiple regression models. The author reported significant findings on behavioral attitude, subjective norms, perceived behavioral control, trust, and persuasive features.

In the fifth chapter, "Mobile Health Integration in Pregnancy," Aslı Günay and Çiğdem Erbuğ investigated the impact of mobile health during pregnancy. To understand pregnant women's interactions with mobile pregnancy applications, they conducted a user study with 33 pregnant women in different trimesters. The study reported that needs, concerns, and expectations change according to different pregnancy trimesters and pregnant women types. Their chapter highlights that the acceptance, adoption, and integration of mobile health into the daily lives of pregnant women; technologies should go beyond that by making expectant mothers feel happy and enhancing their wellness holistically.

In the sixth chapter, "Utilizing mHealth Applications in Emergency Medical Services of Turkey," Görkem Sarıyer and Mustafa Gokalp Ataman presented an exploratory study, providing an overview of the current state of mHealth interventions in emergency medical services (EMS) in Turkey. They outlined the most commonly used technologies in EMS, as well as the challenges and suggestions in EMS use. Utilization of mobile health was reported not being achieved successfully due to several issues as use priorities, costs, legal issues, lack of knowledge, logistics, and problems with technology literacy.

In the seventh chapter, "User Adoption and Evaluation of Mobile Health Applications: The Case for Physical Activity Monitoring," Perin Unal and her colleagues explored the mobile applications that have behavior change support features to encourage physical activity, and they investigated the relationship between user ratings and applications. An empirical analysis of 78 physical activity applications from Google Play store was conducted to extract the features that support behavior change. Minimum redundancy maximum relevance methodology was used to find the most relevant features. The study reported that user downloads are highly related to the features including voice coach, visualization of activity statistics, self-reports, reminders, sharing activity statistics, social platform support, and sharing with community friends.

In the eighth chapter, “Unintended Users, Uses, and Consequences of Mobile Weight Loss Apps: Using Eating Disorders as a Case Study,” Elizabeth V. Eikey sought for an answer for “What do we know about the users of weight loss apps?” and “How do the apps affect users?” In this context, the chapter discussed the unintended users, uses, and consequences of weight loss apps by using eating disorders as a case study. The unintended users of weight loss apps, and then the unintended uses of these apps and the unintended consequences of weight loss apps using qualitative data, including forum posts and interviews, previous work, and popular media articles, were reported.

In the ninth chapter, “Understanding Cross-Cultural Requirements in mHealth Design: Findings of a Usability Study of Indian Health Professionals,” Joyram Chakraborty and his colleagues reported a usability study conducted over 6 months with the participation of eight Indian public health professionals. Their user preferences in their interactions with an mHealth application were investigated using a qualitative analysis approach as a requirement analysis tool to identify cross-cultural factors that might influence usability, accessibility, and interaction challenges and affect mHealth acceptance. In the study, technology familiarity, navigation, language, feedback mechanisms, cognitive overload, and background preferences were reported to be the key factors affecting performance and user acceptance.

In the tenth chapter, “Intention vs. Perception: Understanding the Differences in Physicians’ Attitudes Towards Mobile Health Applications,” Emre Sezgin, Sevgi Özkan Yildirim, and Soner Yildirim reported a comparative analysis for understanding the perception and intention of physicians about mobile health app use. Two different physician groups (mHealth application users and nonusers) were reported outlining the differences in intentions of users and perceptions of nonusers toward actual use of mHealth applications. They pursued a secondary research on a survey data collected from 137 mHealth user physicians and 122 nonuser physicians. Considering the findings, the authors listed a number of suggestions (from psychological, clinical, technological, and regulatory perspectives) to guide developers, researchers, and authorities to identify different factors influencing mHealth app use.

In the 11th chapter, “HealthGuide: A Personalized Mobile Patient Guidance System,” Erhan Eren and Ebru Gökalp presented a mobile application, HealthGuide, which was designed by using a pervasive workflow management system. The authors also regarded the critical technology adoption factors in the mHealth literature. They argued HealthGuide helps improve the user experience and satisfaction by providing personalized services in a timely manner. They featured the app with a case and discussed the benefits and challenges for further implications.

In the 12th chapter, “Mobile Applications User Trend Analysis of Turkish Physicians in Digital Environments,” Elgiz Yılmaz Altuntaş reported the preliminary findings from an online health communication survey about mobile app use trends of Turkish physicians. The study also focuses on discovering the behavior of physicians and the applications they download with respect to healthcare, medical information, and their patient's health history. The findings revealed that the adoption of mHealth is dramatically growing. The author suggested that the improvements in health communication have the potential to play a significant role in the development of a promising new platform for patients/consumers and healthcare providers.

In the 13th chapter, "Acceptance of Mobile Homecare Technologies: An Empirical Investigation on Patients with Chronic Diseases" by Ayşegül Kutlay, Ünal Erkan Mumcuoğlu, and Sevgi Özkan Yildirim, the authors reported the factors affecting the acceptance of mobile homecare system employing unified theory of acceptance and use of technology (UTAUT) as a theoretical model. A survey was conducted and analyzed by using structural equation model. The chapter summarized that performance expectancy was the most significant predictor of patients' intention to use the homecare system. The UTAUT model was also able to explain user acceptance of mobile homecare technology with a variance of 68%.

In the 14th chapter, "Improving Access to Health Services in Sub-Saharan Africa Using Mobile and Wireless Technologies," Emmanuel Eilu presented a literature overview, investigating the use of mobile and wireless technologies in the prevention, surveillance, management, and compliance of disease epidemic in sub-Saharan Africa. The author also summarized the challenges and suggestions about mobile phone technology use and accessibility to health services. This chapter was argued to be resourceful for the authorities to plan and deploy mHealth technologies in sub-Saharan Africa.

In the 15th chapter, "Big Data in mHealth," Mert Onuralp Gökalp and his colleagues investigated the relationship between mHealth and big data concept from a sociotechnical perspective. They reported the opportunities of using big data technologies in the mHealth domain, as well as social and economic implications of using big data technologies. Their study outlined that there are social challenges including privacy, safety, and a false sense of confidence; there are also technical challenges such as security, standardization, correctness, timely analysis, and domain expertise. Finally, the authors proposed a solution framework to facilitate widespread user adoption.

In the 16th chapter, "Adoption of Sensors in Mobile Health," Haluk Altunel reported the use of sensors in mobile health applications. He categorized the sensors as built-in and add-in and investigated the adoption of sensors by different user groups (non-patients and patients) employing usability and user acceptance methods. The author used multiple data collection methods, collecting responses from more than 300 participants. The chapter reported that learnability (the level of ease to accomplish basic tasks the first time they encounter the sensors) was highly correlated with built-in sensors and the use of non-patients. Efficiency was highly correlated with add-in sensors and use of patients.

In the 17th chapter, "Adoption of Internet of Things in Healthcare Organizations," Halil Cicibas and Sevgi Özkan Yildirim addressed Internet of things (IOT) and mobile health adoption in healthcare. They conducted a literature review and identified main variables which affect adoption decision among top-level managers, healthcare professionals, technical staff, and patients. Finally, they presented a number of recommendations for decision-makers to improve the adoption process of its devices in their healthcare organizations. Authors reported that the number of articles addressing radio-frequency identification (RFID) tag adoption is higher than the ones which focus on the other IoT technologies. Thus, they identified the gap in the literature, which needs to be addressed to explain the adoption of healthcare applications by specifically addressing the unique characteristics of IoT technology.

All chapters of this book demonstrate a novel collection of studies presenting the recent research on healthcare and mobile technologies. It covers the adoption and implementation of mobile health technologies for different user groups (e.g., healthcare professionals, patients, and consumers). The book encompasses significant arguments and contributions about the use of mobile technologies, behavioral change, monitoring and tracking, adoption, and different perspectives in mHealth use. The outstanding feature of the book is its perspective toward mobile health. The authors followed a sociotechnical approach in their chapters. Thus, rather than sole technicality, the book also focuses on the users' perspective. Readers who are interested in intention, perception, attitudes, and adoption in mobile health would be interested in this book. The editors believe that this book will be useful for developers, decision-makers, academics, and healthcare providers.

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Part I
Behavioral Change in mHealth

Chapter 2
Use of Persuasion Strategies in Mobile Health Applications

Nurcan Alkiş and Duygu Findik-Coşkunçay

2.1 Introduction

Health-related behaviors have been traditionally influenced through different channels such as television, radio, and newspaper (Michael and Cheuvront 1998). Today, with the advances in the computing technologies, the Internet, e-mail, and mobile applications have become the tools for influencing health-related behaviors. According to Fogg (2007), mobile phones are as powerful as personal computers due to their advantages of providing easy access to the internet and having GPS sensors and other useful instruments such as accelerometers. Therefore, mobile applications present modern opportunities to promote healthy behavior by offering real-time monitoring and detection of a change in health status. The challenge here is to efficiently integrate mobile technologies into daily life to motivate individuals to adopt specific health-related behavior. This could be accomplished by using persuasive technologies.

In the context of social sciences, persuasion refers to changing human behaviors toward a system, an idea, or other people. Simons et al. (2001) defined persuasion as "human communication designed to influence the autonomous judgments and actions of others." Individuals have been trying to influence each other's behaviors

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E. Sezgin et al. (eds.), *Current and Emerging mHealth Technologies*,
https://doi.org/10.1007/978-3-319-73135-3_2

and attitudes unintentionally or intentionally; thus, impact of persuasion can be observed in every part of our lives. For example, marketers use persuasion techniques to increase awareness, charities use for fundraising, and health service providers for healthy behavior. The term persuasion has been introduced to the information systems domain to explain the behavior changes of humans toward computing systems (Fogg 2002). Computing products have been considered as social actor that could trigger behavior change.

In the literature, different persuasion strategies and behavior change theories are employed for mobile health applications. In this study, a literature survey was conducted to identify the theories of behavior change that have been used in mobile health applications. The most common behavior change theories or persuasion approaches were determined as the elaboration likelihood model (ELM), social cognitive theory (SCT), theory of planned behavior (TPB), cognitive behavioral therapy (CBT), transtheoretical model of behavior change, and Cialdini's six principles of persuasion and motivation. Furthermore, the study identified that personalization of applications improves the effectiveness of the applications and increases the success rates of the target behavior. In addition, mobile phone use, e-mail, short message service (SMS) and multimedia message service (MMS) interventions, mobile diaries, mobile phone applications, and mobile games were found to be the commonly used tools to change individuals' health-related behavior in the mobile health domain.

2.2 Review Procedure

A search procedure was defined for a systematic literature review. First of all, English was selected as the only language since the most of the studies in this context were written in English. *Mobile health*, *mobile health applications*, *persuasive technology*, *behavior change*, *behavior change theories*, *behavior change in health*, *persuasion principles*, and *persuasion theories* keywords and their combination were used. The papers were searched using scholar.google.com and the institutional online libraries (i.e., lib.metu.edu.tr and lib.baskent.edu.tr which have access to international databases, such as Scopus, Sciencedirect, and Web of science). In order to reach relevant studies, references of the papers were followed. A total of 76 studies were reached that consisted of journal papers and conference proceedings. The studies that were not focusing on persuasion or behavior change theory and not covering mobile applications were excluded. Finally, 22 of the studies were included for analysis. The next section presented our findings about the theories and mobile applications.

2.3 Persuasion and Behavior Change Theories and Use in Mobile Health Applications

2.3.1 Elaboration Likelihood Model of Persuasion (ELM)

ELM is an attitude change theory. It explains decision-making and persuasion with two parallel processes, of a central and a peripheral route (Cacioppo and Petty 1984; Oinas-Kukkonen and Harjumaa 2008; Petty and Cacioppo 1986). The main idea behind ELM is to decide whether a person will be persuaded from the central or the peripheral route. Central route to persuasion refers to processes, in which elaboration likelihood is high, while peripheral route involves processes with low elaboration likelihood.

ELM has been applied in physical activity interventions in the mobile health domain. In one of the studies, Hurling et al. (2007) proposed a system including the use of the internet, mobile phone, and e-mail to promote physical activity based on the social comparison, decisional balance, elaboration likelihood, and goals. The system used a Bluetooth-connected wrist accelerometer to measure physical activity. In addition, the users were asked to enter their weekly physical exercises, and feedback and a comparison of their performance with other users were provided. The system also provided a schedule for the following week trainings and e-mail or mobile message reminders. Hurling et al. (2007) reported that the system was effective in increasing the physical activity of the users.

Zuercher (2009) integrated ELM into an SMS intervention to increase the physical activity performance of young women. Using this application, the participants sent information about their daily physical activities to a central database via SMS, and they received personal feedback about the exercises and their target goals. The study measured the elaboration likelihood using a scale on the users' motivation, ability, and favorable thoughts. Although a significant correlation was not reported between these constructs and behavior change, the author concluded that SMS was found acceptable intervention method for young women.

2.3.2 Social Cognitive Theory (SCT)

Social cognitive theory (SCT) is a widely accepted and empirically validated model of individual behavior (Compeau et al. 1995). SCT is based on the reciprocally determined factors consisting of environmental influences, cognitive, and other personal factors and behavior. Environmental influences refer to people selecting the environment in which they exist and being influenced by those environments. Furthermore, environmental factors, situational characteristics, cognitive, and other personal factors affect the behavior of individuals. The relations between these three factors, environment, and behavior have been related as "triadic reciprocality" by Bandura (1977) . In addition, Bandura (1986) considered self-efficacy to be a cognitive factor in his theory and defined it as "people's judgments of their capabilities to organize and execute courses of action required to attain designated types of performances. It is concerned not with the skills one has but with judgments of what one can do with whatever skills one possesses." Based on Bandura's theory, Compeau et al. (1999) focused on information systems and developed a model concerning computer usage. The SCT model was used to examine the relations among factors including computer self-efficacy, outcome expectations (performance), outcome expectations (personal), affect, anxiety, and usage. The model shows that self-efficacy directly influences affect, anxiety, and usage, and also it impacts the usage over outcome expectations and effect.

In the literature, it was observed that SCT has been used in the design of health applications, such as using the constructs of SCT on mobile phone intervention (Yoganathan and Kajanan 2013). Zuercher (2009) also used the self-efficacy construct of SCT, alongside with ELM, to assess the positive health behavior change in young women. The author concluded that significant behavior improvement in self-efficacy was not observed.

In another SMS intervention study, Fjeldsoe et al. (2010) implemented SCT in an application called MobileMums to promote physical activity. In this intervention, the researchers developed the content of the SMS considering the constructs of SCT that are effective in changing individual behavior (self-efficacy, goal setting skills, outcome expectancy, social support, and perceived environmental opportunity for physical activity).

2.3.3 Theory of Planned Behavior (TPB)

TPB extended the theory of reasoned action (Ajzen and Fishbein 1975) in order to understand the complexities of human social behavior. The key factor in TPB is the individual's intention to perform a behavior, which means that an individual's behavior is determined by his/her intention to perform that behavior (Ajzen and Fishbein 1975; Chang 1998). Ajzen and Fishbein (1975) theorized that behavioral intention is a function of two conceptually distinct sets of attitude towards behavior and subjective norms of behavior. Attitude is considered a collection of behavioral beliefs, and thus attitude toward behavior refers to the "degree to which a person has a favorable or unfavorable evaluation or appraisal of the behavior in question" (Ajzen 1991). Subjective norm indicates the normative belief and is defined as "the perceived social pressure to perform or not to perform the behavior" (Ajzen 1991). TPB introduced a third independent expositive factor of intention, perceived behavior control, which refers to beliefs that underlie the level of control over behavior and "people's perception of ease or difficulty of performing the behavior of interest" (Ajzen 1991).

Sirriyeh et al. (2010) proposed that the effective components of attitude (such as finding the behavior enjoyable and pleasant) influence engaging in physical activity. They conducted an SMS intervention with adolescents and found that the SMS content was successful in increasing the physical activity of inactive participants. This study demonstrated enjoyment as an influencing factor in promoting physical activity by taking the attitude construct of TPB as the theoretical base.

2.3.4 Cognitive Behavioral Therapy (CBT)

CBT is a kind of psychotherapy involving processes cognitive restructuring, stress inoculation training, problem-solving, skills training and relaxation training (Butler et al. 2006). CBT targets groups to solve their problems and change their behaviors. Self-monitoring is one of the key methods in CBT (Mattila et al. 2008). With this approach, the subjects can be taught the ways that they could observe their actions, emotional reactions, thoughts, and other health-related variables. Through these observations, individuals can identify their behavioral lifestyle changes (Mattila et al. 2008). In the literature, CBT has been implemented in a number of studies as clinical trials and cognitive-behavioral interventions (Butler et al. 2006).

In this context, a mobile phone application, The Patient-Centered Assessment and Counseling Mobile Energy Balance (PmEB),was developed to monitor caloric balance in real time for weight management (Lee et al. 2006; Tsai et al. 2007). The application aimed to increase self-efficacy of self-monitoring in dietary and exercise behavior and helped people to change their nutrition habits. PmEB was developed with a four-phase iterative approach. The first three phases were designed using human-computer interaction methodologies. The users enter their daily consumption of food and the physical activities they undertake into the system, which then calculates the caloric balance. The system also sends reminder SMS messages to motivate the users to update their caloric and exercise information. In the last phase, the researchers assessed the feasibility of the application with 15 clinically overweight and obese participants using two key methods, ubiquitous computing evaluation (attention, trust, conceptual degree, interaction, invisibility, and impact) and feasibility evaluation (compliance and satisfaction). The results of the study demonstrated that self-monitoring increased the level of awareness in all participants. Paper diaries were found to be inconvenient leading to bias and lower compliance, whereas PmEB was easy to use and effective in motivating users in a variety of ways. This application helped users to develop emergent weight management practices. However, the researchers added that PmEB users found food entry challenging and disliked the prompts.

Mattila et al. (2008) developed the wellness diary (WD) for the management of personal wellness and weight based on the philosophy of CBT. WD was used for self-monitoring and embedded in an existing calendar application for life and time management. The focus of the research was on the usage, usability, and acceptance of the concept and its implementations. The study showed that WD was well accepted and actively used by the participants.

Wylie and Coulton (2008) presented a health-monitoring software, Heart Angel, which was developed for mobile phones to monitor, record, and improve individuals' level of fitness. The software included built-in cardiorespiratory tests, a tracking software to provide information about heart rate exertion over time and location. It also provided mobile game called Health Defender, which measures the players' real-time heart rate and informs them about heart rate exertion during game play that triggers bonus points. These bonuses are used to encourage users to undertake a physical exercise to increase their heart rate.

Denning et al. (2009) introduced a wellness management system, BALANCE, which automatically detects the user's caloric expenditure via a sensor from a Mobile Sensing Platform unit worn on the hip for long-term health monitoring. The researchers conducted initial validation experiments to measure oxygen consumption during treadmill walking and jogging. The results showed that the system estimates caloric output within 87% of the actual value. The researchers concluded that this system would facilitate behavioral change for weight loss and weight control.

Morris et al. (2010) aimed to investigate the potentials of mobile phone technologies to increase access using CBT techniques and provide instant support. The researchers developed a mobile phone application, Mood Map, which allowed users to report their moods and the therapeutic exercises they undertook for cognitive reappraisal and physical relaxation. A one-month field study was conducted with eight participants who were prompted to report their moods several times a day using the Mood Map by selecting from mood scales. In addition, the participants were able to activate mobile therapies when needed. The researchers emphasized that use of Mood Map was successful in increasing self-awareness and coping with stress.

Lathia (2012) stated that people use their mobile phones in the lavatory to pass the time; therefore, this is an ideal idle moment to use health applications. The researchers introduced the design of The Poo mobile phone application to examine user feedback about their gastrointestinal health in an idle moment. This application allows users to input data to monitor and review their current bowel movement.

2.3.5 Transtheoretical Model of Behavior Change

The transtheoretical model was derived from theories of psychotherapy and behavior change. This model proposed that health behavior change depends on the progress that occurs in six stages: precontemplation, contemplation, preparation, action, maintenance, and termination (Prochaska and Velicer 1997). In the precontemplation stage, people do not intend to take action in the near future (for 6 months) (Prochaska and Velicer 1997). Persuasive technology should target precontemplators to focus on education (Consolvo et al. 2009). In the contemplation stage, people intend to change their behaviors in the next 6 months (Prochaska and Velicer 1997). For contemplators, persuasive technology should be designed in a way to provide techniques for overcoming barriers and rewards for encouraging desired behaviors (Consolvo et al. 2009). In the preparation stage, people are anticipated to take action in the immediate future (next month) (Prochaska and Velicer 1997). In this case, persuasion technology should focus on rewarding behaviors even if the behavior is not consistent (Consolvo et al. 2009). In the action stage, people have made specific explicit modification in their lifestyles usually within the past 6 months (Prochaska and Velicer 1997). For the people in this stage, the best strategy is to focus on keeping track of progress and consider the elements of social influence (Consolvo et al. 2009). In the maintenance stage, people try to prevent relapse; however, they cannot undergo the change process as frequently as people who are in the action stage (Prochaska and Velicer 1997). For maintainers, persuasion technology should provide strategies for problems encountered previously and help them to realize how they become "the kind of person one wanted to be" (Consolvo et al. 2009; Prochaska et al. 1992, p. 12). In the termination stage, individuals do not have any temptation and have 100% self-efficacy (Prochaska and Velicer 1997). The researchers identified ten processes of change to achieve decisional balance, self-efficacy, and temptations: Consciousness raising, dramatic relief, self-reevaluation, environmental reevaluation, self-liberation, social liberation, counterconditioning, stimulus control, contingency management, and helping relationships (Prochaska and Velicer 1997).

Grimes et al. (2010) created a casual nutrition game called OrderUP!, in which players learn how to make healthier meal choices. The researchers used the transtheoretical model of behavior change to characterize four processes of change, namely, consciousness raising, self-reevaluation, engaging in helping relationships, and counter-conditioning. The researchers assessed the experiences of 12 participants with the game, and they observed that playing OrderUP! helped people to demonstrate behavior change and encouraged them to adopt a healthier lifestyle.

2.3.6 Cialdini's Six Principles of Persuasion

To understand how people influence others' attitudes and actions, Cialdini proposed six principles of influence that triggers the behavior of people (Cialdini 1993, 2001, 2004). According to Cialdini, these basic principles can be taught, learned, and applied to change human behavior in different contexts. These principles were defined as followings:

- The principle of reciprocation: According to this principle, "People repay in kind." This strategy can be applied by giving gifts, doing favors, and making concessions (Cialdini 2003).
- The principle of scarcity: This is based on the assumption that "People want more what they have less." When something is scarce, people have a tendency to value it more. This principle can be applied by explaining the unique benefits of the target behavior, opportunities, and using deadlines. For example, Kaptein and Eckles (2012) applied this strategy in their online bookstore by mentioning that there were only limited copies of the books on sale.
- The principle of authority: People are inclined to follow those who have power. This principle is based on the idea that "people defer to authorities." When a

request is made by a legitimate authority, people have a tendency to follow/believe the request. This principle can be applied by referring to expert opinions in applications.

- The principle of commitment and consistency: "People align with their clear commitments." People do what they are told to do. This strategy can be applied encouraging target users to make public commitments since they will be consistent with their previous commitments.
- The principle of social proof (consensus): This principle depends on people's tendency to follow other people that are similar to them when making a decision. In other words, "People follow the lead of similar others". To apply this principle, examples from similar individuals' behaviors can be given.
- The principle of liking: According to this principle, people are influenced more easily from those they like. This principle can be applied by considering similarity and praise since people like who likes them and behave similarly to those. Groves et al. (1992) identified the factors that increased liking as the similarity of attitude, background, dress, praise, cooperation, and physical attractiveness.

Cialdini's persuasion principles are implemented in different domains to change human behavior. In the mobile health domain, these principles have mostly been used in e-mail and SMS interventions and mobile phone applications. Kaptein et al. (2010) conducted two experiments, in which the participants were asked to join a lunch walk exercise and consume fruit. The researchers employed Cialdini's following persuasion strategies in e-mail messages: authority, scarcity, and consensus. Authority was employed by giving recommendations from the physicians, general practitioners, and the World Health Organization. Scarcity was employed by mentioning the limited slots to join the activity, and consensus was employed by giving examples from similar individuals. The results of the study showed that these strategies increased people's compliance to health-related activities.

Kaptein et al. (2012) used personalized short SMS to reduce snacking. The researchers developed and validated the Susceptibility to Persuasive Strategies scale (STPS) based on the six principles of Cialdini (1993). The researchers performed an experiment with 73 participants. The test group received personalized text messages, and the control group received non-tailored messages. It was observed that, based on the participants' score on STPS, the personalized messages resulted in a higher decrease in the consumption of snacks.

Van Dantzig et al. (2013) aimed to reduce sedentary behavior with the SitCoach application, which encourages office workers to have regular breaks from sitting. This application monitors physical activity and sedentary behavior, and it sends timely persuasive messages suggesting active breaks. The messages were based on the social influence strategies of Cialdini (1993). To evaluate the effectiveness of persuasive text messages, the researchers conducted an experiment with 86 participants from different health companies in the Netherlands. The study showed that there were significant differences between the control group, not receiving any persuasive messages, and the intervention group, receiving advising messages to take a break. However, no significant change was observed in the physical activity of the participants.

Alkiş and Temizel (2015) investigated the relationship between Big Five Personality (BFP) traits and six influence strategies of Cialdini and found that different types of personalities are influenced differently from persuasion strategies which will guide the use of persuasion strategies according to personality type. The study showed that data related to personality is crucial for implementing effective influence strategies for a given personality type. As suggested by Hirsh et al. (2012), persuasive messages are more effective when they are framed according to the personality traits of people. In addition, Halko and Kientz (2010) investigated the relationship between BFP traits and persuasive technologies in the context of health-mobile applications. They found correlations between these traits and cooperative, competitive, positive reinforcement, negative reinforcement, intrinsic, extrinsic, authoritative, and non-authoritative persuasion instruction styles. The results of the study contributed to the personalization of health applications according to the personality types.

2.3.7 Fogg's Behavioral Model (FGM)

FGM was proposed by Fogg (2009) to understand the drivers of human behaviors. There are three factors in this model to determine behavior: motivation, ability, and trigger. According to this model, to achieve a target behavior, the person should be motivated enough, have the ability to accomplish the target behavior, and be triggered to perform the behavior. Therefore, a persuasive design should focus on increasing the motivation for the target behavior, consider the ability of audience, and use effective triggers.

Gasser et al. (2006) compared the usage and acceptance of a mobile lifestyle coaching application with that of an equivalent traditional web application. In the study, the researchers administered a set of health questionnaires that incorporated social facilitation features to enhance motivation. The implications of the study provided a guideline to strengthen the persuasiveness of health applications on mobile devices. The researchers emphasized the importance of using social facilitation features, such as aliases and avatars or functionalities, as instant messaging, for strengthening the persuasive effect of the system.

When the mobile health applications were examined, it was seen that some of these applications aimed to improve users' motivation to reach the target behavior, which is a dimension in FBM. For example, Patrick (2009) performed an SMS and MMS intervention by assessing the motivation progress in order to help individuals improving their dietary behaviors (to lose or maintain their weight over 4 months). The experiment was conducted with age- and a gender-adjusted sample of 65 participants, and it was found that the intervention group that received personalized SMS and MMS messages two to five times a day lost more weight than the control group.

Ahtinen et al. (2009) evaluated user experiences in three mobile wellness applications, namely, Wellness Diary (WD), Mobile Coach (MC), and SelfRelax (SR). In their study, the researchers concentrated on motivational factors. The results indicated that the participants positively responded to the applications. In the study, the participants used the applications to find the solution for given problems. The rate of using the applications increased once the participants understood the purpose of the functions and perceived them as being personally relevant. WD was perceived being easy to use, which means that its purpose and functionalities were understandable. On the other hand, MC was more challenging to understand and to learn. However, it provided persuasive and motivating solutions that can be adaptable for training programs, goals, and coaching. MC triggered curiosity, challenge, and control factors of intrinsic motivation. SR was perceived as being intuitive to use, and it was considered beneficial for helping participants to fall asleep and relax.

Pollak et al. (2010) created the Time to Eat mobile game to motivate children to develop healthy eating habits. The researcher examined the role of the motivational feature of a mobile phone in supporting and encouraging healthy eating habits in seventh and eighth graders. The game allows participants to care for a virtual pet by sending photos of the food they consume. The researcher evaluated the experience of 53 seventh and eighth graders. According to the results, the children who played the game consumed a healthy breakfast more frequently than those who did not play the game.

Buttussi and Chittaro (2010) created a fitness game called Monster & Gold to increase physical exercise. In the game, users gain or lose points according to their level of exercise. This study showed that games have motivational effects on people, which is a dimension of persuasion in FBM.

2.4 Discussion and Implications

With the improvements in technology, health-related behaviors have been promoted in using mobile systems and applications. The extensive use of mobile phones is an evidence of their acceptance as well as an advantage in supporting the adoption of a healthy lifestyle. In the reviewed studies, ten mobile phone applications, six SMS-MMS interventions, four games, and two e-mail interventions cases were investigated. This showed that mobile phone applications are becoming a common medium to promote health behavior. These applications were effective in managing weight, encouraging physical activities and exercises, preventing and managing chronic diseases, self-monitoring, and self-awareness for long-term wellness. Furthermore, promoting physical activities and wellness management were the common target behaviors for the applications.

In order to increase the effectiveness of these applications, behavior change, and persuasion theories were employed. In this study, the following theories and models were identified from the literature review: traditional behavioral theories, specifically ELM, SCT, TPB, CBT, the transtheoretical model of behavior change, Cialdini's six principles of persuasion, and FBM. Among these theories CBT and motivation are frequently implemented.

In addition, the mobile applications that were reported in the studies were revealed that the personalization feature was effective to promote health-related behaviors. For example, Halko and Kientz (2010) listed the persuasive health technology design strategies (authoritative, non-authoritative, cooperative, competitive, extrinsic, intrinsic, negative reinforcement, and positive reinforcement) and suggested that different types of personalities required different strategies to be considered in designing effective personalized applications. Similarly, the personalized feature of mobile game increases its effectiveness as a persuasive application.

For example, a mobile game called MoviPill was designed to increase medication adherence for elder people in that regard (De Oliveira et al. 2010). In the game, users gain points when they take their bills on time and at the right amount, and they compete against other users.

This study revealed that health behavior change was difficult to measure and quantify. Therefore, it was not always possible to determine whether the applications were successful solutions in achieving the intended behavior (Klasnja et al. 2011). Thus, regardless of the platform (mobile phones, web applications, or social networking tools), health-related applications should be carefully designed and implemented to reach the target behavior.

2.5 Conclusion

In this chapter, the studies on mobile health applications, behavior change, and persuasion theories were investigated. ELM, SCT, TPB, CBT, transtheoretical model of behavior change, Cialdini's six principles of persuasion, and FBM were the theories employed in mobile health applications. Persuasive technology, including SMS-MMS intervention, e-mail intervention, mobile health applications, and games, encourages individuals to adopt a healthy lifestyle by helping them track their physical activities, moderate their diet, reduce the consumption of snack food, learn how to make healthier meal choices, and prevent and manage chronic diseases. This chapter provides an overview for (1) researchers to guide their future research and (2) persuasive technology designers to develop effective mobile health systems to promote behavior change.

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Chapter 3
Behavior Change Techniques Used in Mobile Applications Targeting Physical Activity: A Systematic Review

Hakan Kuru

3.1 Introduction

Most of the individuals today are health-care consumers, and with the advances in technology, e-health is changing the delivery of health care. mHealth has emerged as a component of e-health, and it was defined as the use of information and communication technology (ICT) such as smartphones, personal computers, global positioning services (GPS), and vital sign monitors for health care and health services (World Health Organization 2011). mHealth apps serve for two primary purposes: disease management and wellness/fitness. The wellness-focused mobile applications (mApps) facilitate health-promoting behaviors. In 2015, 38% of the mHealth applications in the Apple Store and Google Store were grouped under the fitness category (Ventola 2014). For disease management, mApp features allow health professionals to maintain low-cost interventions. These interventions include reminders and motivational messages. Moreover, the interventions can target different ages, sexes, occupations, motivational stages, and physical abilities. The major function of mApps, therefore, is to encourage and support consumers to adopt healthy behaviors (Free et al. 2013). Furthermore, mApps enable self-monitoring, health tracking, and creating social connection (Klasnja and Pratt 2012).

The need for technologies that promote physical activity behavior was a result of physical inactivity. According to the World Health Organization report, the lack of physical activity was related to 3.2 million deaths annually, which was the reason for increased mortality risk by 20–30% (World Health Organization 2009). In 2010, it was reported that one in four adults participated less than the recommended 150 min of moderate physical activity per week (World Health Organization 2010). In order to overcome this problem, public health researchers have been focusing on novel approaches to change physical activity behavior.

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E. Sezgin et al. (eds.), *Current and Emerging mHealth Technologies*,
https://doi.org/10.1007/978-3-319-73135-3_3

The impact of apps on changing the physical activity behavior is currently unknown (Yang et al. 2015). Besides, most apps have not been designed on grounded health behavior theories and evaluated using scientific methods (Cowan et al. 2013; Direito et al. 2014; Middelweerd et al. 2014). Thus, identifying the BCTs would illuminate the way of adopting mApps for modifying physical activity behavior. Besides, understanding the way of adoption will provide insight on developing and designing mHealth interventions. Physicians and practitioners who seek low-cost interventions would also benefit from the findings of BCTs used in mApps. This systematic review aimed to examine the use of behavior change techniques in smartphone apps that target physical activity based on an established taxonomy of behavior change techniques.

3.2 Background

To be successful in health behavior interventions and to maximize the effectiveness of mobile apps, we need to investigate the effective ways in development. To develop an understanding about how interventions work, Abraham and Michie (2008) studied the BCTs in their taxonomy by investigating different health behavior theories. For instance, the technique that *prompted specific goal setting* was derived from the control theory; or the technique that *provided information about others' approval* was derived from the theory of reasoned action, the theory of planned behavior, and the information-motivation-behavioral skills model. Therefore, in their taxonomy, a variety of health behavior theories were used (i.e., the theory of reasoned action, the theory of planned behavior, social cognitive theory, the information-motivation-behavioral skills model, the control theory, operant conditioning, and theories of social comparison) (Abraham and Michie 2008).

In their taxonomy, the theory of reasoned action proposes that the behaviors are under a person's control and the behavioral intentions predict the actual behavior (Fishbein and Ajzen 1975). Intentions are determined by two factors: attitude toward the behavior and beliefs regarding other people's support of the behavior. The theory of planned behavior explains the behavior as individual's perceived control over the opportunities, resources, and skills that are needed to be performed for affecting behavioral intentions (Ajzen 1991). Social cognitive theory explains human behavior as behavior change, which is caused by the interactions between the environment, personal factors, and attributes of the behavior itself. Also, self-efficacy is explained as one of the most important characteristics that determine the behavior change (Bandura 1997). The information-motivation-behavioral skills model mainly focuses on the cognitive domain by using the information to support behavior change. Control theory, being one of the motivational theories, states that behavior is stimulated by what individuals desire the most: survival, love, power, freedom, or any other needs (Carver and Scheier 1982). The operant conditioning theory focuses on changes in observable behaviors and explains that new or continued behaviors are impacted by new or continued consequences (Skinner 1974).

Theories of social comparison discuss how individuals evaluate their opinions and abilities by comparing themselves to others to reduce uncertainty in these domains and learn how to define the self (Berkman and Syme 1979).

3.3 Method

This study aimed to review the empirical literature on the behavior change techniques employed in mobile apps within the physical activity context. This systematic review started with searching combination of keywords: "behavior change technique-related keywords" AND "mobile application-related keywords" AND "physical activity."

More specifically, the keywords of behavior change techniques and mobile applications were combinations of the following: "behavior change" OR "behaviour change techniques" OR "behavior change techniques" OR "BCT" OR "BCT taxonomy" AND "mobile applications" OR "smartphone applications" OR "mApps" OR "mobile apps" OR "smartphone apps." EBSCOhost, Web of Science, and Google Scholar databases were used for the search. The literature research was conducted in August and October 2016. The articles included were only in English. The flowchart of the search process and refinement was given in Fig. 3.1.

3.3.1 Inclusion and Exclusion Criteria

This review includes only the studies focusing on the BCTs used in mobile applications in the context of physical activity. This focus was decided after a preliminary search of the literature about health behavior theories and the efficacy of behavior changing in mobile applications. Reporting an analysis of the behavior change techniques in the context of mobile application development and grounding the method on a developed taxonomy were the main criteria for the study selection.

3.3.2 Coding of BCTs

The selected studies used three different BCT taxonomies: the original Abraham and Michie's taxonomy, the CALO-RE taxonomy, and the behavior change technique taxonomy (v1) (Abraham and Michie 2008; Michie et al. 2011). The numbers and definitions of BCTs differed from each other in these taxonomies, and this led to inconsistencies when investigating differences of the BCTs. To achieve consistency, the first taxonomy of Abraham and Michie's original work, comprising 26 items, was chosen as the reference taxonomy, as shown in Table 3.1 (Abraham and Michie 2008). The reason for the selection of this taxonomy was that the other two

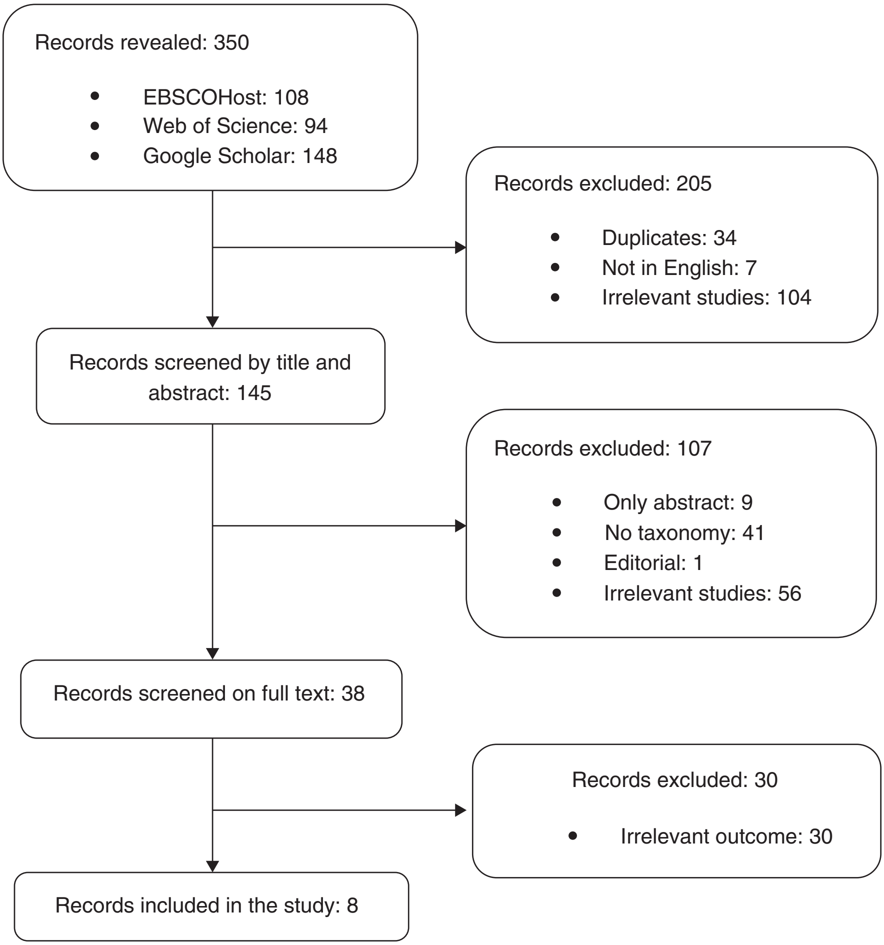

Fig. 3.1 Selection of the studies

taxonomies, the CALO-RE taxonomy and the behavior change technique taxonomy (v1), were derived from this reference taxonomy and covered more items of BCTs. For example, the CALO-RE taxonomy includes 40 items, and the behavior change technique taxonomy (v1) lists 93 items. This indicates a challenge in terms of standardization. For example, in the CALO-RE taxonomy, technique *goal setting* was explained in two different ways: *goal setting (outcome)* and *goal setting (behavior)*. On the other hand, Abraham and Michie's first taxonomy defined *goal setting* in one item, covering both *goal-setting behavior* and *goal-setting outcomes*. Therefore, the first taxonomy, which is composed of a relatively fewer number of BCT items, was selected for coding.

In the next step, the 93-item taxonomy and 40-item taxonomy were coded in line with the 26-item taxonomy. For example, the techniques in 93-item taxonomy,

Table 3.1 Abraham and Michie's taxonomy of BCTs

	Technique and theoretical framework	Definition
1	Provide information about behavior-health link (IMB)	General information about behavioral risk. For example, susceptibility to poor health outcomes or mortality risk in relation to the behavior
2	Provide information on consequences (TRA, TPB, SCogT, IMB)	Information about the benefits and costs of action or inaction, focusing on what will happen if a person does or does not perform the behavior
3	Provide information about others' approval (TRA, TPB, IMB)	Information about what others think about a person's behavior and whether others will approve or disapprove of any proposed behavior change
4	Prompt intention formation (TRA, TPB, SCogT, IMB)	Encouraging a person to decide to act or to set a general goal. For example, to make a behavioral resolution such as "I will take more exercise next week"
5	Prompt barrier identification (SCogT)	Identify barriers to performing the behavior and plan ways of overcoming them
6	Provide general encouragement (SCogT)	Praising or rewarding a person for effort or performance without this being contingent on specified behaviors or standards of performance
7	Set graded tasks (SCogT)	To set easy tasks and to increase difficulty until target behavior is performed
8	Provide instruction (SCogT)	Telling a person how to perform a behavior and preparatory behaviors
9	Model or demonstrate the behavior (SCogT)	An expert shows a person how to perform a behavior correctly. For example, in class or on video
10	Prompt specific goal setting (CT)	Involving detailed planning of what a person will do, including a definition of the behavior specifying frequency, intensity, or duration and specification of at least one context, that is, where, when, how, or with whom
11	Prompt review of behavioral goals (CT)	Review and reconsideration of previously set goals or intentions
12	Prompt self-monitoring of behavior (CT)	Asking a person to keep a record of specified behavior(s) (e.g., in a diary)
13	Provide feedback on performance (CT)	Providing data about recorded behavior or evaluating performance about a set standard or others' performance (e.g., the person received feedback on their behavior)
14	Provide contingent rewards (OC)	Praise, encouragement, or material rewards that are explicitly linked to the achievement of specified behaviors
15	Teach to use prompts or cues (OC)	Teaching a person to identify environmental cues that can be used to remind them to perform a behavior, including times of day or elements of contexts
16	Agree on behavioral contract (OC)	Agreement on a contract specifying behavior to be performed so that there is a written record of the person's resolution witnessed by another
17	Prompt practice (OC)	Prompting a person to rehearse and repeat the behavior or preparatory behaviors

(continued)

Table 3.1 (continued)

	Technique and theoretical framework	Definition
18	Use follow-up prompts	Contacting the person again after the main part of the intervention is complete
19	Provide opportunities for social comparison (SCompT)	Facilitating observation of non-expert others' performance. For example, in a group class or using video or case study
20	Plan social support or social change (social support theories)	Prompting consideration of how others could change their behavior to offer the person help or (instrumental) social support, including "buddy" systems and/or providing social support
21	Prompt identification as a role model	Indicating how the person may be an example to others and influence their behavior or provide an opportunity for the person to set a good example
22	Prompt self-talk	Encourage the use of self-instruction and self-encouragement (aloud or silently) to support action
23	Relapse prevention (relapse prevention therapy)	Following initial change, help identify situations likely to result in readopting risk behaviors or failure to maintain new behaviors and help the person plan to avoid or manage these situations
24	Stress management (stress theories)	Being involved in a variety of specific techniques (e.g., progressive relaxation) that do not target the behavior but seek to reduce anxiety and stress
25	Motivational interviewing	Prompting the person to provide self-motivating statements and evaluations of their behavior to minimize resistance to change
26	Time management	Helping the person make time for the behavior (e.g., to fit it into a daily schedule)

IMB information-motivation-behavioral skills model, *TRA* theory of reasoned action, *TPB* theory of planned behavior, *SCogT* social cognitive theory, *CT* control theory, *OC* operant conditioning

self-monitoring of the outcome of behavior and *self-monitoring of behavior*, were synthesized and coded as *prompt self-monitoring of behavior*. The coded versions of the included studies are given in Appendix.

Abraham and Michie presented 26 definitions of BCTs used in health behavior change interventions based on theoretical frameworks including theory of reasoned action (Fishbein and Ajzen 1975), theory of planned behavior (Ajzen 1991), social cognitive theory (Bandura 1997), the information-motivation-behavioral skills model (Fisher and Fisher 1992), control theory (Carver and Scheier 1982), operant conditioning (Skinner 1974), related goal theories (Austin and Vancouver 1996; Gollwitzer 1999; Locke and Latham 2002), theories of social comparison (Festinger 1954), and theoretical accounts of the impact of social support on health-related behaviors (Berkman and Syme 1979). However, five items in this taxonomy were not grounded in any health behavior theory.

Table 3.2 Studies included in the review

	Reference	Number of apps	Reliability checked	Taxonomy[a]	Location	BCTs per app
1	Yang et al. (2015)	100	Yes	3	USA	6
2	Middelweerd et al. (2014)	64	Yes	1	NDL	5
3	Conroy et al. (2014)	167	Yes	2	USA	4
4	Direito et al. (2014)	40	Yes	1	NZ	8
5	Mercer et al. (2016)	13	Yes	2 + 3	USA	NA
6	Bardus et al. (2016)	23	Yes	1	USA	10
7	Brannon and Cushing (2014)	14	Yes	1	UK	NA
8	Lyons et al. (2014)	13	Yes	2 + 3	USA	NA

[a]1 = Abraham and Michie's first taxonomy, 2 = CALO-RE taxonomy, 3 = CT taxonomy v1

3.3.3 Data Extraction

Following a review of titles and abstracts, 350 potentially relevant articles were identified. From these, eight satisfied the inclusion criteria after a full-text review. In Table 3.2, the following information for each study was pointed out:

- The number of apps reviewed
- Reliability of the study
- The taxonomy used in the study
- The country of the application store
- The number of BCTs for each reviewed app

3.4 Results

The average number of techniques per app was six. When the results for BCTs are analyzed, the overall results revealed that all BCTs in the taxonomy were used at least once. *Motivational interviewing, prompting self-talk,* and *time management* were used only once; *agreement on the behavioral contract* and *relapse prevention* were the only BCTs that were used twice. The findings indicated that *providing feedback on performance* was the most frequently used BCT. After that, *prompting specific goal setting* is the second, and *providing instruction* was the third in the most commonly used BCT. Social support provision and self-monitoring were the fourth and fifth most common BCTs, respectively. The results of the BCTs used in the studies were presented in Table 3.3 (details about frequencies were given in Appendix). The least frequent BCTs in the included studies were not grounded in health behavior theories. For example, *time management*, *relapse prevention*, *prompt self-talk*, and *motivational interviewing* were not derived from any health behavior theory.

Table 3.3 Results of the study

	BCT	Frequency	Theory	Frequency
1	Provide feedback on performance	353	CT	1108
2	Prompt specific goal setting	294	SCogT	972
3	Provide instruction	277	TRA	332
4	Plan social support or social change	269	TPB	332
5	Prompt self-monitoring of behavior	258	IMB	332
6	Model or demonstrate behavior	208	OC	280
7	Prompt review of behavioral goals	203	SCompT	162
8	Provide opportunities for social comparison	162		
9	Provide contingent rewards	155		
10	Provide information about others' approval	140		
11	Set graded tasks	135		
12	Provide information on consequences	108		
13	Prompt practice	90		
14	Provide general encouragement	85		
15	Prompt intention formation	84		
16	Prompt identification as a role model	55		
17	Teach to use prompts or cues	34		
18	Prompt barrier identification	26		
19	Provide information about behavior-health link	25		
20	Use follow-up prompts	7		
21	Stress management	5		
22	Motivational interviewing	2		
23	Prompt self-talk	2		
24	Time management	2		
25	Agree on behavioral contract	1		
26	Relapse prevention	1		

Results regarding health behavior theories showed that the control theory is the most commonly used; the social cognitive theory is second; the theories of reasoned action, planned behavior, and information-motivation-behavioral skills model are third, fourth, and fifth, respectively; the operant conditioning is the sixth; and the social comparison theory is the seventh most frequently used health behavior theory.

3.5 Discussion and Conclusion

This chapter evaluates the use of BCTs in smartphone apps that target physical activity, based on an established taxonomy of BCTs. Eight studies were included in the review, and the results revealed an average of 6.7 BCTs per app. *Providing feedback on performance*, *prompting specific goal setting*, and *providing instruction* were the most frequently used BCTs in the reviewed apps, but they were not grounded in health behavior theory. Apps showed lacks in the use of theoretical constructs (West et al. 2012; Cowan et al. 2013). This finding suggested that app developers should make an effort to apply health behavior theories to some extent.

The most frequently used BCTs are *feedback on performance*, *goal setting*, *providing instruction*, *social support*, and *self-monitoring*. The interventions that included a combination of self-monitoring, goal setting, and providing feedback resulted in a larger effect size (Michie et al. 2009). Moreover, providing knowledge through interactivity (instruction and information) was mostly used method in changing behavior, as it contributed to self-efficacy that initiated intentions to be active (Bandura 1989). This was the outcome desired by mApp users (Kuru 2016). Although embedded accelerometers allowed smartphones to sense different types of movement, self-monitoring and self-reporting need to be used more frequently. Furthermore, action planning and time management needed to be included to support behavior change (Kuru and İnce 2017). Implementing a theory-based combination of BCTs in mApps would maximize the effectiveness of mApps in the mHealth domain.

With regard to the findings concerning health behavior theories, control theory and social cognitive theory were the most frequently observed health behavior theories in this review. However, control theory was considered to be improper for human application; different studies have indicated that the concepts informing this theory are not appropriate for humans (Sandelands et al. 1991). mApp developers need to be careful about applying control theory when developing mApps for health behaviors. On the other hand, the social cognitive theory was effectively integrated into different physical activities and health behavior interventions (Wallace et al. 2000; Ince 2008; Michie et al. 2009). Social support has been shown to be useful for increasing motivation or providing fortification for changes in behavior (Elder et al. 1999). The effectiveness of health behavior theories in mApps needs to be investigated, and a combination of BCTs related to specific health behavior theory should be implemented.

This study is one of the first systematic reviews examining the behavior change techniques used in mobile applications that target physical activity. A strength of this study was that it covered the apps that were found in various application stores in different countries. This vast scope of the review allowed for the generalization of the findings. A limitation of this study was the lack of the trans-theoretical model, health belief model, or social ecological model, which are health behavior theories (Hochbaum 1958; Bronfenbrenner 1994; Prochaska and Velicer 1997). These theories were frequently used for physical activity and health behavior change interventions (Dunn et al. 1998; Hillsdon et al. 2005). The taxonomy used in this review did not offer any BCT, based on the aforementioned theories.

Furthermore, apps have a changing and developing nature with technology. Hence, the findings need to be checked periodically to make legitimate predictions of apps. Further research is necessary since there is not enough information available to evaluate the effectiveness of health behavior theories and BCTs used in mApps targeting physical activity.

Appendix. The Frequency of BCTs in the Studies

BCT	Yang et al. (2015)	Middelweerd et al. (2014)	Conroy et al. (2014)	Direito et al. (2014)	Mercer et al. (2016)	Bardus et al. (2016)	Brannon and Cushing (2014)	Lyons et al. (2014)	Frequency
Provide feedback on performance	97	64	83	52	7	33	2	15	353
Prompt specific goal setting	53	40	103	38	4	32	3	21	294
Provide instruction	37	14	111	84	4	9	13	5	277
Plan social support or social change	84	37	61	55	7	11		14	269
Prompt self-monitoring of behavior	51	62	17	60	7	20	12	29	258
Model or demonstrate behavior	47	7	88	52	1	2	11		208
Prompt review of behavioral goals	23	4	69	22	15	44	13	13	203
Provide opportunities for social comparison	35	10	26	55	14	8	6	8	162
Provide contingent rewards	38	31	24	25	19	4	3	11	155
Provide information about others' approval	64		46	8	7	7		8	140
Set graded tasks	33	3	22	70		2		5	135
Provide information on consequences	13		10	52	5	16		12	108

Prompt practice	5	12	18	45	3	7			90
Provide general encouragement	34			35			3	13	85
Prompt intention formation	10	6	5	50	7	5	1		84
Prompt identification as a role model				55					55
Teach to use prompts or cues	3	1	13		4	6		7	34
Prompt barrier identification	15		6	2	1	1		1	26
Provide information about behavior-health link	13	12							25
Use follow-up prompts		2		5					7
Stress management				5					5
Motivational interviewing				2					2
Prompt self-talk				2					2
Time management		2							2
Agree on behavioral contract		1							1
Relapse prevention			1						1

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Chapter 4
Exploring Intention on Continuous Use of Mobile Health Applications Designed by Persuasive Technology: "Adimsayar" Case Study

Seray Öney Doğanyiğit

4.1 Introduction

Over the past decade, we have seen a rise in the technologies targeting promotion of a healthy life. There are currently over 97,000 health-related applications in total available in the health and fitness category of Apple App Store and Google Play Store, with around 1000 more being created on a monthly basis (Becker et al. 2014). The majority of the popular health applications have been developed for the use of general public, and they target health and wellness promotion, as well as disease prevention. Some of them are free to download, while others require a nominal or substantial charge (Fitzgerald and McClelland 2017). For the paid apps, cost alone is not indication for the quality or effectiveness, and the number of downloads doesn't mean a success for free apps.

With such a wide range of applications—from fitness-monitoring wristbands to doctor-patient communication tools—the mobile health application field has been a great source of both inspiration and design strategies (Zhuang 2013). The types of applications available in application stores show that developers were divided into two groups based on their field of interest, as general tracking tool developers and fitness/nutrition application developers. General tracking apps target individuals interested in healthcare or in monitoring their own health; and the individuals in the latter group constitute the most of the population subgroup in the mHealth market. Other applications focus on managing medical conditions, for assisting people and patients who are interested in healthcare, according to their needs (Research2guidance 2012). Although mobile health apps have been increasing in popularity, and they have been widely used in healthcare, most of these applications failed in a short span of time to keep the user to continue using them.

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E. Sezgin et al. (eds.), *Current and Emerging mHealth Technologies*,
https://doi.org/10.1007/978-3-319-73135-3_4

According to a survey conducted in 2011 by Consumer Health Information Corporation (CHIC), smartphone applications, most of the time, were abandoned by their users, with 26% used only once and 74% abandoned after several times of usage. The same survey also showed that 26% of smartphone applications achieved consumer loyalty and were used continuously (CHIC 2011).

The success of an application depends on how persuasive that application is in changing a behavior. In fact, there are many factors that play a role in an application's ability to change behavior. Factors that influence behavior change, such as design, content, evidence base, relevance to user need, motivation, self-efficacy, user acceptability, beliefs of peers and family, and the role of social support networks, are the main drivers. An application may employ all or some of these aspects. Furthermore, understanding of how and why an individual considers and adopts behavior change is also important. So, developing a strong evidence base and behavior change theory has been important to prevent any failure (Fitzgerald and McClelland 2017).

The long-term utilization of applications is significant for the nature of changes in behavior, since the behavior change is a complex and long-term process with high relapse rates. Therefore, the process is an important factor which should be taken in consideration by the application developers while developing healthcare applications. It would not be proper for the researchers to claim that the participants of their studies have changed their habits unless they actually conducted longitudinal studies (Klasnja et al. 2011). For this reason, applications should be evaluated at frequent and regular intervals to ensure that the user's long-term needs have been fulfilled and the success is sustainable with measurable strategies (Fogg 2009). Accordingly, new design guides and a better understanding of how technologies can be customized to benefit users' lives are required (Halko and Kientz 2010). In this study, the target group of the application, the usage behavior of the target group, and the characteristics that motivate the individual to continue using the application were investigated through an application that was designed in accordance with the specifications of persuasive technology. As mentioned above, there were many basic factors to persuade an individual to change their behavior. This application has been designed and presented to the users with most of these factors considered. While all these features were being investigated, the aim was to give the developers guidelines about the aspects that should be considered in the application as well as key points for technical and behavioral aspects to assist while designing the application.

4.2 Theoretical Background

Until today, numerous research areas were used—e.g., behavior research, environmental psychology, and persuasion—in designing mobile health application technologies upon the needs of individuals. Moreover, theories from social psychology have been used widely for predicting user intentions and behaviors, including Ajzen's theory of planned behavior (Ajzen 2013), Bandura's social cognitive theory and self-efficacy theory (Bandura 1977, 1986), and Davis' technology acceptance model (Davis 1989). Some theories tried to explain the relation between attitude and behavior, other theories explained the persuasion process more generally, and some theories focus on a narrower area of persuasion (Harri and Harjumaa 2008). In addition to these theories, in 2002, B.J. Fogg introduced computer's power to motivate and change behaviors to the research community. This method is called captology, which is the acronym of computers as persuasive technologies (Fogg 2003). All these theories can be used once or multiple times in a study depending on what the researcher needed to measure in the study. Here, the motivation to use the application was assessed first, and then the effect of this motivation on the intention to continue using this application was examined. Additionally, the trust factor was also considered, while the intention to continue the behavior was being analyzed. To evaluate the influential factors on motivation of application use and intention of users toward continuous usage, a hybrid model based on Ajzen's theory of planned behavior and Fogg's captology was proposed. Information about the theories and variables used in this study were provided below.

Theory of planned behavior (TPB) is the most frequently used social psychology theory. TPB is a theory that has been empirically tested in an extensive way in explaining behaviors. According to the theory, human behavior is guided by three kinds of considerations: beliefs about the consequences of the behavior (behavioral beliefs), beliefs about the normative expectations of others (normative beliefs), and beliefs about the presence of factors that may facilitate or impede performance of the behavior (control beliefs). In their respective aggregates, behavioral beliefs produce a favorable or unfavorable attitude toward the behavior; normative beliefs result in perceived social pressure or subjective norm; and control beliefs give rise to perceived behavioral control. In combination, attitude toward the behavior, subjective norm, and perception of behavioral control lead to the formation of a behavioral intention. As a general rule, the more favorable the attitude and subjective norm, and the greater the perceived control, the stronger should be the person's intention to perform the behavior in question (Ajzen 1991). In order to establish a unique model for the purpose of comprehending the motivation of the user behavior toward the application, this study employed theory of planned behavior.

Computer persuasive technology (captology) is used by the studies on the examination of information technologies' power of leading their users to a certain behavior, and therefore shapes, strengthens, or changes their attitudes. Besides devices being used for performing certain actions and considered as resources for acquiring information and establishing communication, computers, as persuasive technology products, are also considered social actors. With the powerful role they play in human life, computers have been turning into devices that persuade users of performing certain behaviors or direct them. The most important aspect that distinguishes this methodology from other behavior theories is that the persuasion process has been shaped through user-machine interactivity (Fogg 2003). In his study, Fogg defined seven persuasive strategies as reduction, tunneling, tailoring, suggestion, self-monitoring, surveillance, and conditioning. Reduction—simplifies a task that the user is trying to do. Tunneling—guides the user through a sequence of activities, step by step. Tailoring—provides custom information and feedback to the user based on their actions. Suggestion—gives suggestions to the user at the right moment and in the right context. Self-monitoring—enables the user to track his own behavior to change it to achieve a predetermined outcome. Surveillance—observes the user overtly in order to increase a target behavior. Conditioning—relies on providing reinforcement (or punishments) to the user in order to increase a target behavior (Fogg 2003).

Persuasive technologies have been used in the healthcare field, for motivating people to adopt healthier routines, guiding them to take protective measures to prevent diseases, or monitoring health problems such as diabetes, high blood pressure, and coronary diseases. Today, there are numerous mobile health applications available that are designed in accordance with persuasive technologies. For instance, applications that can be categorized among these are UbiFit (Consolvo et al. 2007), Runkeeper (Zhuang 2013), and Be Well Mobile (Boland 2007), which were designed in accordance with some or all of the seven persuasive strategies of Fogg's captology (Fogg 2003). UbiFit Garden is an application which aims to encourage people to live a healthy lifestyle by participating in regular physical activity. Runkeeper is an application that allows user to track activities, measure their performance over time, and share progress with their friends while doing it. Be Well Mobile is a diabetes management application for teens and children. It aims to support patients in self-management behaviors.

Out of these, self-monitoring—tracking one's own activities—has been the most prevalent one, and most of the systems for changing health behavior included this component. Conditioning—usually by means of positive reinforcement, but sometimes also with punishment—was another common strategy (Klasnja et al. 2011).

Motivation of application use can be defined as the driving force behind all the actions of an individual. The influence of an individual's needs and desires both have a strong impact on the direction of their behavior. Motivation is based on individual's emotions and achievement-related goals. In this model, motivation of application use was defined as the motivation of behavior. According to Ajzen's TPB model (Ajzen 1991) the more favorable the attitude and subjective norm, and the greater the perceived control, the stronger the person's intention to perform the behavior in question should be. All combinations of these variables also present motivational factors that capture how hard people are willing to try to perform a behavior in this model. Additionally, the application having persuasive properties is another quality that motivates the users to use it. In the Fogg's behavior model (Fogg 2009), Fogg asserted that for a person to perform a target behavior, he or she must (i) be sufficiently motivated, (ii) has the ability to perform the behavior, and (iii) be triggered to perform the behavior. These three factors must occur at the same moment; else the behavior will not be performed. The trigger feature mentioned here referred to the application feature that sends the reminders and messages with suggestions. The ability feature referred to the application's facilitating features such as counting the steps of the individuals and showing them their performance at certain intervals. The individuals can be persuaded that they can use the application if they perceive how simple it is to use. The captology principle here was another factor that increases the motivation to use the application, as the facilitating and triggering features that Fogg specified in the FBM.

Trust has become the main concern when using persuasive technologies. Persuasive messages have been most effective when received from a known and trusted source (McGraa 2010). Trust is the belief that the trustee will act cooperatively to fulfill the trustor's expectations without exploiting their vulnerabilities (Pavlou and Fygenson 2006). Trust signifies belief, reliability, dependability, and confidence toward an object or process (Fogg 2003). The belief that the application does not share any data with anyone without user approval will prove that the person/company that has developed the application considers the privacy of their users. Once a user believes that data provided through the application are reliable, it shows that the user also believes that the person/company offers correct and valid information from reliable resources (Gefen 2002). In this study, trust for getting information referred to a consumer's belief that the application will provide valid, accurate, and timely information.

Even though Fogg stated that unintended consequences are not included in the captology (Fogg 2003) that can cause ethical disputes, all the communication processes based on human-machine interaction will be questioned for the factor of trust. Obviously, the users' trust in human-machine interaction, as well as in persuasive technology, could potentially be affected by numerous factors. The lack of trust in this communication may lead to using of the application inefficiently, which will result in a weakness in its effectiveness. Therefore, the lack of trust has been a prominent reason that affects whether a user will use technology, such as persuasive applications, or not. All variables used in the study provided indications about the consequences of the psychological, environmental, and technical factors that are important in understanding the nature of behavior change through the use of application. By testing the way these components work, it becomes possible to understand which works better or which one is less effective. Some discussions, on the other hand, asserted that persuasive technologies establish an asymmetric communication with the users. In other words, persuasive technologies do not intend to establish an open communication with the user by receiving feedback from them but merely to provide information. This brings along the ethical discussions and the necessity of questioning the persuasive technologies in terms of reliability and questioning if they are manipulative technologies (Nickel and Spahn 2012). The main objective of designing persuasive technologies for such areas must be to direct users to more positive behavior changes, and to support users about turning the behavior into a daily routine in the long term, without needing that technology.

4.3 Research Model

To be used in this study, an application is introduced. It has been developed in Turkish and can be downloaded to smartphones and tablets, and it aims to motivate users to monitor their health. The application, namely, "Adimsayar," has been selected for this study in line with the objectives of the research, such as having Turkish interface, downloaded mostly by Turkish users, having the ability to maintain bidirectional contact with the users, and being designed in accordance with persuasive technology principles. The application aims to encourage the user to get into the habit of exercising and walking as daily routines and by counting the steps the user has taken throughout the day. Then, it sends data via customized messages and enables users to share their data on social networks such as Facebook and Twitter. Adimsayar rewards users for meeting their daily activity goals, with a smiling face on the screen background of their mobile phone. By using suggestion strategy at the right time, Adimsayar gives daily nutrition suggestions to the users as they approach their goals. The application was released in early 2011. During the planning stage of this research, the application had already been downloaded by 77,000 users. It was downloaded by around 127,000 users by the end of 2015. However, since most of the unpaid applications in Turkey have been rated based on the number of downloads, the application's influence over individuals becomes harder to estimate.

This study was planned in three sections as user demographics, application usage, and the factors that influence the intention of users on using the application continuously. There were three types of questions utilized in total: five-point Likert scale, multiple choice, and fill in the blanks. The first part was comprised of demographic questions in order to analyze the target user group, such as age, gender, marital status, education, household income, and employment status. The second part was comprised of the questions of Francis (Francis et al. 2004) on behavior, with the purpose of monitoring the mobile health application behaviors of the users who have downloaded the application. In the third part, in order to examine the continuous use, Ajzen's theory of planned behavior and Fogg's captology principles were used (see Fig. 4.1). Questions related to attitude, subjective norm, and perceived behavioral control were adopted from Ajzen's model (Ajzen 2013). The scale of captology designed by the author was inspired by Fogg's study of persuasive technology (Fogg 2003). The questions on motivation to use the application (Ajzen 2013; Fogg 2009) and on intention toward continuation of the behavior were prepared by the author as well. In addition to this, taking inspiration from the studies analyzing trust's impact on intention (Pavlou and Fygenson 2006), we proposed that trust might be an important factor on the intention of continuing to use the application. For this reason, trust was included to the model as a moderator variable.

For *theory of planned behavior (TPB),* the variables motivating individuals to use the health application with the purpose of achieving the desired health behavior

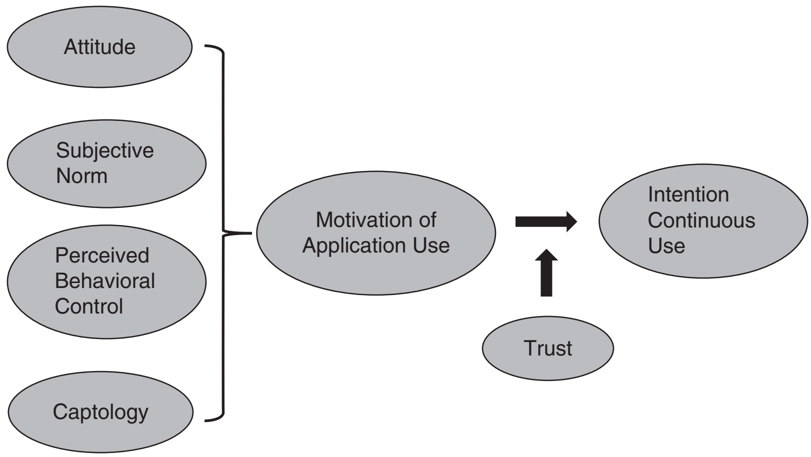

Fig. 4.1 Theory of planned behavior and captology hybrid model

were identified within the scope of the factors in TPB, which influence the motivation of application use. Therefore, the following hypotheses were proposed:

H1: Individual's belief that mobile applications support healthy living increases their health motivation toward using that application.
H2: Approval of utilization of an application by relatives (subjective norm) increases the individual's health motivation toward using that application.
H3: Perceiving mobile health applications' ease of use (perceived behavioral control) increases their health motivation toward using that application.

Captology refers to the persuasive technologies that are used in this study and are being used for increasing the motivation of the individual (enhancing their motivation capacity), to download the application. By using seven items of captology, the following hypothesis was formulated:

H4: The features offered by the mobile health application, such as reduction, tunneling, tailoring, suggestion, self-monitoring, surveillance, and conditioning, increase the motivation of the individual toward using that application.

Motivation of application use refers to the influence of subjective norm, perceived control, attitude, and captology on the intention of continuous behavior in this study. Therefore, the following hypothesis was proposed:

H5: The increment in the motivation of individuals toward using mobile health applications influences their intention to continue their behavior of using that application.

Trust refers to the belief that the application will provide valid, accurate, and timely information and the belief that the owner of application cares about privacy of their users and users' feedback. Therefore, the following hypothesis was proposed:

H6: Trust in the application moderates the relationship between motivation of the individual on using mobile health applications and their intention to continue using the application.

4.4 Research Method

4.4.1 Data Collection and Subject Characteristics

The research was carried out between the dates of 24th of June 2013 and 29th of July 2013. Within this 6-week period, the research was announced with survey links distributed via weekly reports, sent to users' personal mail accounts, displaying main page of the official website and in Facebook posts. Designed as a single section, the questionnaire consisted of 33 questions in total. Attitudes were measured with five questions, subjective norm with two, perceived behavioral control with three, captology with seven, motivation with two, trust with three, and intentional continuous use with only one question. The survey link was clicked by 1023 people and was filled out by 255. In the first part, in order to analyze target behavior, we asked users about their characteristics. The demographics of users are as shown in Table 4.1.

Almost half (51%) of 255 participants were female, and 42% were male. 51% of the participants were married, and 44% were unmarried. It can be seen that the people who have filled out the survey were distributed in the categories in a balanced way, with regard to their gender and marital status. When the distribution was examined in terms of age groups, it was observed that 24% of people who used Adimsayar application were young people aged between 18 and 25, which constituted the group involving the highest number of users.

Looking at the educational background, it can be seen that the majority (54%) was either university graduates or highly educated people. When we categorized the groups in terms of their incomes, it was possible to say that the category with the highest number of people falling was (25%) in the group of middle income, which was TRY2001 to TRY3000. An analysis of the participants based on their occupations showed that they were identified as self-employed (15%), students (14%), other occupations (12%), engineers (9%), teachers (6%), health professionals (%6), housewives (5%), civil servants (4%), financiers (4%), academicians (3%), and retired (3%). It can be observed that the occupation percentage results and the distribution in the categories of educational backgrounds, incomes, and age groups were in alignment.

Table 4.1 Adimsayar users' demographics ($n = 255$)

Characteristics	n	%
Gender		
Female	131	51
Male	107	42
Unanswered	17	7
Marital status		
Married	131	51
Unmarried	113	44
Unanswered	11	4
Age		
18–25	61	24
26–30	37	15
31–35	50	20
36–45	46	18
46 and above	48	19
Unanswered	13	5
Monthly income		
TRY0–1000	50	20
TRY1001–2000	56	22
TRY2001–3000	63	25
TRY3001–4000	22	9
TRY4001 and higher	41	16
Unanswered	23	9
Educational background		
Primary school	4	2
Secondary school	8	3
High school	64	25
Bachelor's degree	138	54
Postgraduate	31	12
Unanswered	10	4
Occupation		
Self-employed	39	15
Student	35	14
Engineer	24	9
Teacher	16	6
Health professional	16	6
Housewife	12	5
Civil servant	11	4
Financier	9	4
Academician	8	3
Retired	8	3
Other	30	12
Unanswered	47	18

Table 4.2 Adimsayar usage period ($n = 255$)

Application usage periods	n	%
Less than 1 month	88	35
Between 1 and 3 months	60	24
Between 3 and 6 months	40	16
Between 6 and 12 months	36	14
Between 1 and 2 years	24	9
Unanswered	7	3

Table 4.3 Adimsayar application usage frequency ($n = 255$)

Application usage frequencies	n	%
Rarely (1–2 times a year)	54	21
Sometimes (1–2 times a month)	43	17
Occasionally (1–2 times a week)	45	18
Often (more than 2 times a week)	36	14
Always (everyday)	68	27
Unanswered	9	4

4.4.2 Adimsayar Usage Periods and Frequencies

In this part, in order to monitor user behavior, we asked users for how long and how often they use the application. The numbers representing when and how often the participants use Adimsayar application are as shown in Tables 4.2 and 4.3.

In Table 4.2, of the 255 participants, 35% have used the application for less than 1 month, 24% have used the application for 1–3 months, 16% have used the application for 3–6 months, 14% have used the application for 6–12 months, and 9% have used it for 1–2 years.

In Table 4.3, of the 255 participants, 27% used the application every day, 21% used the application once or twice a year, 18% used the application once or twice a week, 17% used the application once or twice a month, and 14% used the application more than twice a week. Adimsayar application period and frequency relation is shown in Fig. 4.2.

When the correlation between application usage periods and frequencies was assessed, it was observed that two contrary data sets were coming to light, indicating that among the users who used the application for less than 1 month, 28% always use it, and other 28% of them used it rarely. It can be observed that the usage of frequency "always" was the one having the highest number of users (36%). The usage frequencies of users who used the application for a period of 3–6 months were distributed evenly. Among the users who used the application for a period of 6–12 months (28%), the usage frequency "rarely" was the highest. However, two contrary usage frequency data sets were obtained when the data was examined in regard to usage frequencies of the users. Some participants used the application for a period of 1–2 years and stated as (33%) "always" and some (29%) "rarely."

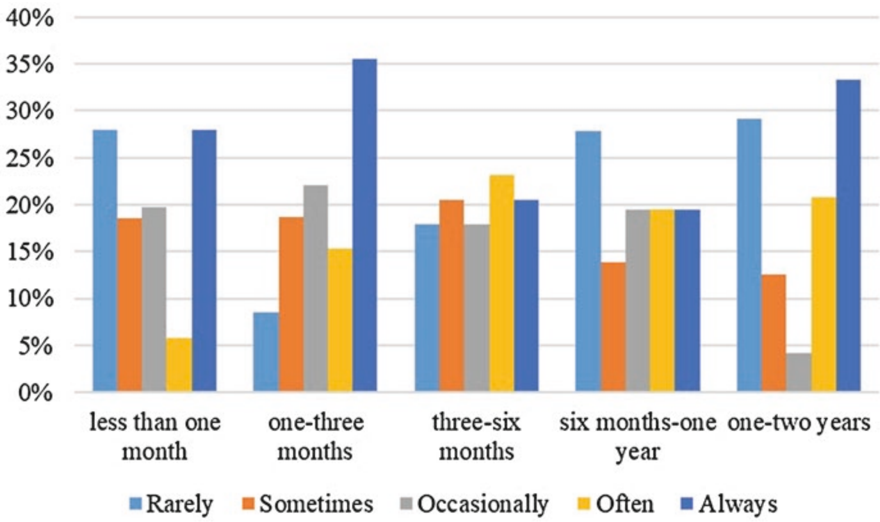

Fig. 4.2 Adimsayar usage periods and frequencies ($n = 255$)

4.5 Data Analysis and Results

In this part, in order to investigate the intention of continuous use, we analyzed the results of hybrid model.

4.5.1 Reliability

Survey results have been analyzed through the program, Statistical Package for the Social Sciences (SPSS) 18.0 for Windows. In the testing process of the criterion's reliability, it was tested whether there was a correlation between the answers given to expressions constituting the criteria. In addition, one of the most frequently used coefficients in reliability analyses, alpha coefficient (Cronbach's alpha), was used in the determination of the correlation. In order to be able to say at the end of the analysis that the construct is reliable, the value attached to the alpha coefficient was expected to be higher than 0.60 and even close to 0.70 (Tull and Hawkins 1993; Tavşancil 2002). The reliability analysis of the constructs used in this study has been carried out according to this principle, and the alpha coefficient calculations are presented in Table 4.4. Therefore, subjective norm was excluded from the model.

Table 4.4 Adimsayar application reliability criteria table

Variables	Alpha coefficient (Cronbach's alpha)
Motivation toward using health application	0.806
Attitude toward behavior	0.864
Subjective norm	0.497
Perceived behavioral control	0.824
Trust	0.812
Captology	0.942

Table 4.5 Multiple regression results of motivation to use mobile health applications and attitude, belief in control, and captology

	Standard β	R^2	Adj. R^2	F	p
Personal attitude	0.40				
Perceived behavioral control	0.17				
Captology	0.33	0.616	0.611	134	0.00

4.5.2 Results

In the evaluation of the research hypotheses, the correlation between personal attitude, perceived behavioral control, captology, and motivation of using mobile health applications has been tested with the multiple regression analysis technique (see Table 4.5). To be able to conduct a multiple regression analysis, firstly, the linearity and multicollinearity among variables were checked. Correlations among all constructs were analyzed, and the correlation coefficient ranges between 0.597 and 0.70. A collinearity diagnostic test using tolerance and variance inflation factor (VIF) was conducted. If the tolerance value was less than 0.10, the item should be dropped from the analysis due to multicollinearity (Hair et al. 2010). As a rule of thumb, when the VIF of a variable exceeds ten, then a serious multicollinearity problem was expected (Mason and Perreault 1991). Briefly, in order not to have multiple correlations, the VIF value must be less than 10, and the tolerance value must be greater than 0.10. In the data set, the VIF value was found to be lower than 10 and the tolerance value (distributed between 1.991 and 3.995), and it was found to be greater than the critical value of 0.10. In addition, residual plots were drawn to check error terms related to regression equation, and it was observed that residuals had random patterns and they were not correlated with other variables.

Motivation of using mobile health applications and intention of continuous use of application have been tested with the multiple regression analysis technique shown in the Table 4.5. As in the single regression model, the determinant coefficient R^2 was closer to 1, which was expected to be more appropriate (Cohen 1988). The independent variables that affected the health application usage motivation-dependent variable of the research can be seen in Table 4.5.

Table 4.6 Hierarchical regression analysis of the motivation to use health applications and intention to continue with the application via trust

	Standard β	p	R^2	Adj. R^2	R^2 change	F	p
Model 1			0.383	0.38	0.38	145	0.00
Motivation	0.619	0.00					
Model 2			0.536	0.53	0.06	93	0.00
Motivation	0.466	0.00					
Trust	0.287	0.00					
Model 3			0.442	0.437	0.09	90	0.00
Motivation	0.353	0.00					
Trust	0.274	0.00					
MXT	−0.33	0.00					

The following are the results of hypotheses testing:

H1: Personal attitude toward that mobile health application will support healthy life and increase their motivation toward using that application. There was a positive and meaningful connection between personal attitude and motivation to use health applications and ($\beta = 0.40$; $p = 0.000$).

H3: Perceived behavioral control increases individual's health motivation toward using that application. There was a positive and meaningful connection between perceived behavioral control and motivation to use health applications ($\beta = 0.17$; $p = 0.02$).

H4: The features offered by mobile health applications, such as reduction, tunneling, tailoring, suggestion, self-monitoring, surveillance, and conditioning, increase individual's motivation toward using that application. There was a positive and meaningful connection between captology and motivation to use health applications ($\beta = 0.33$; $p = 0.000$).

Personal attitude, perceived behavioral control, and captology all together explained 61% of the change in motivation to use health applications ($R^2 = 0.611$; $F = 134$, $p = 0.000$).

H5: The increment in individual's motivation toward using mobile health applications influenced their intention to continue their behavior of using that application.

H6: Individual's trust in mobile health applications strengthened the influence of motivation toward using mobile health applications, on the intention toward continuing to use that application.

In this line, moderating effect of "trust" has been tested for its influence on motivation and continuous use with the hierarchical regression analysis technique (see Table 4.6).

As suggested in the literature, through hierarchical regression analysis, the independent variables were entered into the equation in steps (or blocks), with each independent variable being assessed about their contribution to the prediction of the dependent variable, after the previous variables have been controlled for (Pallant 2007).

As seen in Model 1 in Table 4.6, motivation toward using health applications explained 38% of the intention toward continuing the behavior by itself ($R^2 = 0.38$, $F = 145$, $p = 0.00$), and there was a positive and significant relationship between motivation to use health applications and intention to continue the behavior (βmotivation = 0.559, $p = 0.00$). In the second model, trust was added to this model, and motivation and trust together explained 53% of intention toward continuing the behavior ($R^2 = 0.53$, $F = 93$, $p = 0.00$, βmotivation = 0.47, p-motivation = 0.000, βtrust = 0.29, p-trust = 0.000).

In order to consider the moderator effect of trust on the relationship between motivation and intention toward continuing behavior, interaction effect of independent and moderator variables was examined (MXT) in the third model, and it was added to Model 3. As a result trust was found to decrease the power of the association between motivation to use health applications and intention to continue the behavior (change in $R^2 = 0.09$, $p = 0.00$, β motivation * trust = −0.33, p-motivation * trust = 0.000).

4.6 Discussion and Future Work

The goal of this article was to analyze an application multidimensionality and to provide designers a guidance ensuring sustainable use of applications.

In the first section of this study, it was observed that the target audience of Adimsayar consisted of highly educated people (54% university graduates or people of higher education) and young people between 18 and 25 years old. It has been reported in a research on mobile application usage carried out in Turkey that both genders with younger ages (<35 years old) use wellness and fitness applications, and these people are more likely to be highly educated (Doganyigit and Yilmaz 2015). Considering that the people who use these complicated mobile health applications were aware of protecting and managing their health, thus, our research finding indicating that more than half of the users were educated individuals was in alignment with the literature.

In the second section of this study, considering the result of the majority who use the application for a period of less than 1 month, the users in this category were divided into two profiles, as the ones using the application "rarely" and "always." Based on this result, we might be looking at two different types of user behavior, categorized as the ones who download the application and start using it and the ones who try the application and stop using it. Receiving feedback about why users do not use the application continuously, or the features of the application they like, especially within the interval of the first month, expected to suggest significant clues in respect to design and development of the application. Another factor that has to be taken into consideration at this point was the necessity for the application developers to determine certain periods in accordance with the purposes of the application and to develop the right strategies for their applications. Considering that the increment (58%) in the number of Adimsayar users in a period of less than 1 month overlaps the period between June and July when the survey was published, it was assumed that the application's purpose of motivating people to exercise fits users' needs for the summer. In time, it became clearer whether the users are going to continue using the application after 3 months. During the threshold between the third and the sixth month, the user did either become an active user and continuously used the application or they stop using the application. Therefore, it is advised that the developers should keep monitoring user activities frequently during the first 3 months rather than only during the first month. What has to be done at the beginning was to develop a number of tools through which the users can submit their feedback. Weekly reports and integration with social media platforms can be given among such solutions. Another significant point is that the application might be frustrating when it does not meet the needs of the users, and this may cause the user to not only stop using the application but also to quit achieving their goals of health behavior. In this regard, taking this responsibility into account, the developers must maintain in close contact with the users. Beyond creating an application, through which they can know their users better and that regards users' demands, the aim of the developers must be to turn their application into a customizable health support.

In the third section of this study, the factors employed for determining users' intention toward continuing to use the application were analyzed. The factor that primarily boosted users' motivation to use Adimsayar application was that about starting to use the application to get healthier (personal attitude). The secondary factor was the persuasive features of the program (captology features); the third factor was complexity or simplicity of the application. In cases where the individuals have determinant personalities with high motivation, they can perform the behavior, although they might not be skilled enough to use the application (Fogg 2009).

Trust, employed as a moderator in this study, caused decreasing of the influence of motivation toward using the application. That is to say, although motivation strengthened the intention toward continuing to use the application, when the trust factor came into play, the level of motivation became a less determining factor. Put simply, as the reliability of the application increased from the perspective of the user, their need for motivation diminished. This study showed that the trust in the application alone can be a reason for the user to continue using an application. Therefore, an application developer should thoroughly explain the purposes of their application and what kind of conveniences the application will offer to the user. This also showed that it will be beneficial for the corporations, which have earned the trust of the public (like ministries, NGOs, private corporations, etc.), to use their awareness in play when developing applications. The results of these studies also revealed that, in the long term, with the future increments in the utilization of such applications, data confidentiality and privacy need to be considered, as well as the necessity of establishing new regulations with this regard.

The application used in this study, Adimsayar, was a free-of-charge health promotion-oriented application. Thus, it is suggested to also utilize paid applications developed for different purposes (medical conditions: diabetes, high blood pressure, etc.) for future efforts to investigate motivational factors. Furthermore, it is suggested to analyze the sustainable impacts of these applications as well.

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Part II
Monitoring and Tracking with mHealth

Chapter 5
Mobile Health Integration in Pregnancy

Asli Günay and Çiğdem Erbuğ

5.1 Introduction

It goes without saying that healthcare is one of the most important matters in human life. Pursuing a healthy life can be considered the utmost aim of individuals, as it is highly related to their quality of life. Women's and children's health hold an important place in healthcare due to their crucial role in the development of society (Ki-Moon 2010). The health of mothers is considerably prominent, as motherhood is one of the essential stages in life (Balaam et al. 2013). Thus, prenatal care—healthcare during pregnancy—is a key element in facilitating a safe pregnancy and maternal health (Amnesty International 2010). Nevertheless, until very recently, it was observed that the resources spent for women's and children's health have fallen short. Investing in women's and children's health would help to build stable, peaceful, and productive societies (Ki-moon 2010). Furthermore, increasing the investment would have many benefits, such as increasing productivity and economic development, decreasing poverty, and realizing primary human rights (Ki-moon 2010).

The main concern of maternal healthcare is to eliminate or at least minimize maternal mortality and maternal morbidity. However, every year hundreds of women suffer or die due to preventable pregnancy and childbirth complications (Ki-moon 2010; Megalingam et al. 2013; mHealth Alliance 2012; Zero Mothers Die 2014). A number of barriers hinder women from receiving proper maternal services, which can be listed as personal, economic, bureaucratic, educational, and other barriers. (1) Personal barriers are related to women's health conditions and how they perceive and cope with them. Most pregnant and childbearing women have reported new and continuing health concerns (Childbirth Connection 2009) since bearing a

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E. Sezgin et al. (eds.), *Current and Emerging mHealth Technologies*,
https://doi.org/10.1007/978-3-319-73135-3_5

child and becoming a mother alter a woman's entire life in a distinct way. Physical changes in women's bodies and psychological changes during pregnancy can create a barrier against them in receiving the care they need. They may tend to feel physically exhausted, emotionally weak, and lonely (Barclay et al. 1997). It is even more challenging if they are experiencing their first childbirth. All of these factors may result in a woman seeking maternal care information which may be misleading or not timely. In that regard, pregnant women might have inaccurate information and pass it to one another (Maniam et al. 2007), or they might not act timely and wait until the last stages of pregnancy to demand care. Thus, it can create a gap in care, even though continuous care is of great significance from prepregnancy to the postpartum period (Peyton et al. 2014). (2) Financial circumstances pose a significant challenge, especially in developing countries and rural areas, as expenses related to maternal care exceed the costs of many other healthcare conditions (Childbirth Connection 2009). Women in such places are more prone to pregnancy-related risks regarding economic barriers for receiving proper and timely care (mHealth Alliance 2012). (3) Bureaucratic issues also create a barrier. For instance, troublesome and expensive documentation procedures, in-person communications, administrative requirements, and insufficient care providers can hinder women from accessing prenatal care and maintaining a healthy pregnancy (Amnesty International 2010). (4) A lack of education and awareness can negatively impact pregnancy management. Most women are not aware of the importance of early prenatal care, and even though they have to receive support and education in the first trimester, they tend to visit doctors more frequently in the final trimester. Thus, it creates a gap in care. (5) For other barriers, location and language may limit accessing care. These barriers are mostly effective for the women living in developing countries and rural areas, as it is typically hard for them to access available resources due to technology, literacy, and language barriers (Loxton et al. 2007).

Despite aforementioned barriers, women's pregnancy and childbirth experiences have been changing. This occurs in parallel to the changes in the information and communication technologies, such as the Internet, which have altered the lifestyle of societies (Maniam et al. 2007). Now, technologies have an increasing role in pregnancy and motherhood (Balaam et al. 2013). Hence, the human–computer interaction (HCI) discipline has been searching for novel technologies in supporting pregnancy and has been trying to understand the role of technology in the motherhood (Balaam et al. 2013). According to the United Nations International Children's Emergency Fund (UNICEF), the strategic use of mobile technologies can eliminate many barriers and solve diverse problems related to time, distance, and coordination in the delivery of maternal health services (mHealth Alliance 2012; UNICEF Stories of Innovation 2012).

In the subsequent sections of this chapter, changing experiences were addressed by referring to the description and utilization of mHealth and orientation toward positive user experiences. Second, an exploration of user experiences with mHealth technologies for pregnancy with a user study was presented as reporting the data collection and analysis. Finally, elicited positive user experience dimensions were demonstrated by discussing the qualities and components of mHealth technologies for pregnancy and the temporal needs and expectations of pregnant women. These aspects were considered crucial to inform the design and generate happier pregnancy experiences.

5.2 Changing Experiences

As aforementioned, a wide-scale transformation in health systems has been ongoing with a shift toward personalized healthcare. This implied that users' experiences with the technologies have been also reshaped in tandem with personalized technologies. Thus, users' experiences with mHealth have been at the junction point of interdisciplinary areas such as technology, design, and health. Therefore, looking at changing experiences in conceptual and practical terms through the perspectives of different areas, it is worthy to investigate the current state of the pregnant users' experiences with mHealth technologies. In this section, the major changes were presented by reporting a brief background of mHealth technologies, current utilization of mHealth technologies in healthcare and pregnancy, and the shift in user experience and design (based on the literature about positive experiences with the influence from the positive psychology discipline).

5.2.1 mHealth Technologies: A Brief Background

There were multiple terms in the literature that have been used interchangeably to emphasize personal healthcare delivery models, even though there have been slight differences among them based on historical developments, underlying technologies, or related research fields. For instance, telemedicine, telehealth, telecare, e-health, mHealth, wireless health, personal health informatics, and similar terms have been used interchangeably to refer to the management of healthcare in a personalized manner and with a remote access (Meier et al. 2013). mHealth has emerged with the widespread use and utilization of wireless, innovative, and mobile systems to enhance healthcare services, health outcomes, and healthcare research (WHO 2011). However, mHealth has not had a commonly used single definition. In that regard, some researchers mentioned that it is an umbrella term to encapsulate all technologies from videoconferencing to remote and mobile monitoring, whereas others embraced a narrower description adhering merely to mobile health applications.

Considering the previous use of the term "mHealth," it has appeared in the studies of unwired electronic medicine (Istepanian et al. 2000), shaping the healthcare domain in parallel with the improvements in wireless network technologies (Pattichis et al. 2002; Jovanov et al. 2003). During its earliest implementations, the mHealth concept was associated mostly with wireless biomonitoring involving physiological parameters. With the miniaturization of technologies, increased availability of wireless networks and enhanced performances and data rates have widened the application range of mHealth. Hence, that has accelerated the acceptance and adoption of the mobile systems in healthcare domain. Recently, mHealth also encompassed the monitoring of physical activities to track behaviors, actions, locations, and falls (Budinger 2003; Istepanian 2004). Moreover, mHealth systems were suggested to be stand-alone applications or parts of a body area network (BAN) (Boulos et al. 2011). BANs typically involved sensors on different parts of the body to conduct physiological and/or physical parameter measurements. The data collected by BAN were transferred to the personal healthcare device and then to the remote healthcare professionals' systems in order to respond to the related healthcare situation properly (Jovanov 2005; Varshney 2009).

So, although there has been no strict definition until now, it can be implied that the preceding healthcare concepts such as telemedicine, telehealth, telecare, and e-health may not necessarily include mobility while providing remote healthcare services; yet, mHealth has been almost entirely about mobile and wireless systems, products, and applications such as personal digital assistants (PDAs), smartphones, smartphone applications, mobile electronic devices (MEDs), and wearable systems (Istepanian 2004; Free et al. 2010; Congdon 2013).

5.2.2 The Practice of mHealth Technologies in Pregnancy

Current trends and technologies have been promoting the application use in mHealth during healthcare practice. Connecting the patients, healthcare professionals, and other providers, offering tailored information, and providing location-independent services have been some of the trends in healthcare (Bental et al. 1999; Dodero et al. 2001; Britze 2005). These trends have affected the trends in maternal care as well. Such trends focused on the use of mobile devices and mHealth which had great potential to promote the improvements in pregnancy care worldwide (mHealth Alliance 2012; Ki-moon 2010; WHO 2011). The World Health Organization (2011) has also stated mHealth technologies as one of the promising approaches for pregnancy management, training, education, and interventions. Regarding the WHO guidelines, mHealth was also suggested to close the gap between the medical and domestic care during pregnancy. Among diverse mobile technologies, smartphones and smartphone applications have taken the lead as they have already been indispensable parts of our lives. Currently, there are billions of mobile devices and smartphones around the world including the rural areas. In addition, more than 100 countries have consulted to mHealth in order to attain better care (Ki-moon 2010). Increasing number of smartphone applications have also started to be integrated into people's lives ubiquitously with healthcare and management tools (mHealth Alliance 2012). Ever-increasing numbers of healthcare applications in smartphone application stores have been an indication of the significant role of mHealth in healthcare. Fortunately, pregnancy has been one of the prominent healthcare topics that was started to get attention from the application developers (Johnghorban and Shirali-Shahreza 2013; Peyton et al. 2014).

Providing consultation via mHealth had far-reaching benefits in maternal care to transcend healthcare barriers apart from the previously mentioned opportunities. Primarily, mHealth technologies being available to every person regardless of location or time minimized the psychological pressure and stress on pregnant women in care. The reason was that mHealth can help with immediate pregnancy-related complications that might be critical both for the women's and the children's health. This ease of access could promote pregnancy awareness and education for everyone, including rural and poor areas, because such technologies have been getting more and more cost-effective (Maniam et al. 2007; Ki-moon 2010; mHealth Alliance 2012; Zero Mothers Die 2014). Moreover, mHealth can also be convenient in terms of offering the diverse set of options for considering diverse needs during pregnancy (Bental et al. 1999; Maniam et al. 2007; Balaam et al. 2013). For instance, different information and care attention might be needed during different stages of the pregnancy (CenterSite 1995–2007), and mobile phone applications can provide the required flexibility, portability, and personalization (Johnghorban and Shirali-Shahreza 2013). This is also more beneficial and convenient than accessing widely available generic and complicated information in printed form (Maniam et al. 2007). Furthermore, providing a better preparation setup for childbirth, keeping better track of both the baby and women (Balaam et al. 2013), supporting social connectivity and sharing experiences (Hui and Ly 2012), and even stimulating pregnancy and better pregnancy management (Kosaka et al. 2011) can be counted as the additional benefits.

However, although maternal care and pregnancy-related issues have been the key focus for mHealth studies and implementations worldwide (Peyton et al. 2014), there has been a gap in the literature regarding the use of healthcare technologies for pregnancy. mHealth and pregnancy literature concentrated mostly on the least developed countries. More specifically, some of these studies attracted attention for the significance of educating women about pregnancy in the least developed countries (e.g., Maniam et al. 2007; WHO 2011; mHealth Alliance 2012), and others demonstrated real-world cases, initiatives, and projects about utilizing basic mobile services, such as free mobile information services and SMS consultations as part of government actions and national health agendas (e.g., Ki-moon 2010; WHO 2011; Tamrat and Kachnowski 2012; Megalingam et al. 2013). Peyton et al. (2014) highlighted the excessive focus on pregnancy for the least developed and developing countries in the literature, which overlooked the need for pregnancy care in developed countries. Furthermore, most of the studies and existing applications ignored the role of the spouse (Peyton et al. 2014). During the pregnancy, fathers' experiences were also reported as valuable, and even though they can overlap with the experiences of the pregnant women to a certain extent, they had mostly distinctive characteristics. It was reported that pregnancy is not only demanding for the pregnant women, but it is equally stressful for the spouses (Maniam et al. 2007). On the other side, there has been a lack of information about the needs and related support during the first trimester of the pregnancy, although pregnancy management should have started at the early stages for better care (Peyton et al. 2014).

Despite the aforementioned gaps in the literature, technologies and applications related to pregnancy and maternal care have been investigated and developed over the time. Some researchers have attempted to group and categorize these technologies. In that regard, Johnghorban and Shirali-Shahreza (2013) categorized the pregnancy applications in the Google store by considering their functions, such as becoming pregnant, pregnancy information, pregnancy tracking, and pregnancy support. These functions were about to help women to become pregnant; to give general information about the processes of the pregnancy (such as fetal development); to help women to track pregnancy issues like weight gain, contraction, and kick times; and to provide extra support by offering nutrition and exercise tips. Peyton et al. (2014) focused on a broader picture by making categorizations about seeking information about pregnancy, social sharing, and the role of the partners. Nonetheless, users' expectations from these pregnancy-related mobile technologies, their needs, concerns, and expected features of these technologies have not yet been studied holistically or systematically. Thus, in spite of unceasing efforts and escalating numbers of pregnancy-related mobile solutions and the indispensable place of mobile technologies in today's world, pregnancy-related mobile solutions still need further investigation and development for being integrated into the daily lives of pregnant women. Therefore, it is valuable to concentrate on the ways that mobile pregnancy applications can be effectively integrated into the daily lives of pregnant women.

5.2.3 Toward More Positive User Experiences

It is crucial to investigate user experiences holistically because technology-driven and problem-focused solutions cannot be sufficient to warrant the effective integration of mobile pregnancy applications into the daily lives of pregnant women. Solutions could be successful only when they improve the wellness and well-being of pregnant women and promote their well-being. With appropriate user experience and design research, not only personal needs and expectations, which go beyond pragmatic issues, can be determined but also possibility-driven solutions, which go beyond problem-driven solutions, can be put forward.

Such a perspective aiming to affect people positively, to increase their wellness and life quality, would require to focus on the positive psychology discipline. Although the roots of better life studies reach back to the early times (Peterson 2006; McMahon 2008), the study for better life and the related concepts constituted considerably a novel research area. Positive psychology is one of the most recent and promising fields in the psychology discipline. In essence, psychology had three fundamental goals: treating mental diseases, increasing the well-being of relatively less troubled people, and promoting genius and talent (Seligman et al. 2004). Nevertheless, after World War II, psychology started to neglect the most positive goals and focused merely and extensively on the former one, treating mental diseases. Years later, during his presidency of the American Psychological Association in 1998, Seligman highlighted the necessity of increasing the bar of human functioning and giving equivalent value to studying what is right with people, rather than only what is wrong with them, and named the relevant field “positive psychology” (Peterson 2006).

The act of shifting focus from the negative to the positive has started to echo in diverse disciplines like economics, education, philosophy, HCI, and design. In particular, the concepts of “positive design” (Desmet and Pohlmeyer 2013), “positive technology” (Riva et al. 2016), and “positive informatics” (Calvo et al. 2016) came to prominence in HCI and design disciplines only very recently.

In reality, the holistic user experience perspective, which highlights the significance of hedonic experiences as much as pragmatic experiences, has dominated the design discipline for more than a decade (Hassenzahl and Tractinsky 2006; Desmet and Hekkert 2007; Schifferstein and Hekkert 2008). Achieving positive experiences rather than dealing with negative experiences in those holistic experiences has become the major objective in user experience studies (Hassenzahl and Tractinsky 2006). No wonder that it was expected from all technological advances and design solutions to have positive outcomes. Yet, in the nascent positive technology, positive design, and positive informatics areas, creating solutions that enhance wellness and happiness is the central objective at the onset, not a positive side effect. That’s why different from the conventional approaches which focus on problems as a starting point, these areas defined possibilities and opportunities as a starting point and then purposefully utilize suitable methods and tools. It is named as the “possibility-driven design” approach (Desmet and Pohlmeyer 2013).

5.3 Exploration of User Experience with mHealth Technologies for Pregnancy

The literature findings, challenges, and opportunities that were mentioned in the previous sections have indicated the necessity of a new point of view toward mobile pregnancy technologies that would support the wellness and well-being of pregnant women holistically and positively. Eventually, this was expected to be, in return, an effective integration of mobile pregnancy technologies into the daily lives of pregnant women. In that regard, considering the difficulty in comprehending the reflections of changing experiences and the lack of evidence in the literature about the dimensions of positive user experience with mobile pregnancy technologies, an empirical study was designed. In the following sections, the methodology of the study, data collection, and analysis procedures were presented.

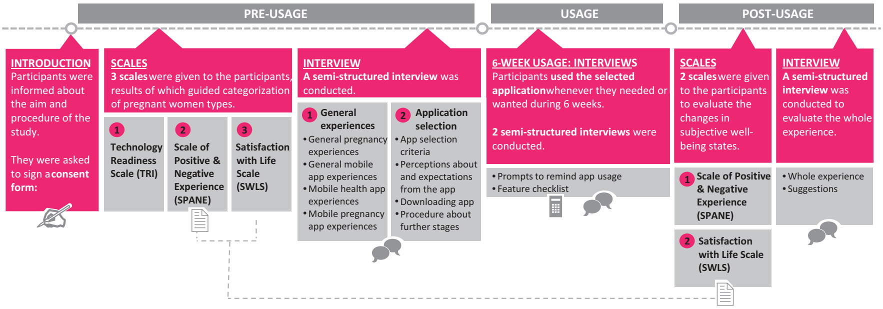

Fig. 5.1 The methodology

5.3.1 *Methodology*

The study was conducted with pregnant women in Turkey. The aim was to explore how the acceptance, effective integration, and sustained use of mobile pregnancy applications in the daily lives of pregnant women, can be realited, and how the design can make mobile pregnancy applications become an integrated part of pregnant women's lives. The methodology of the study is illustrated in Fig. 5.1.

The study was composed of three main stages: pre-usage, usage, and post-usage. The experiences of users are influenced not only by the moments of direct interaction. In fact, the user experiences are holistic and dynamic, extending over time and encompassing the entire periods of the pre-usage and post-usage stages (Karapanos et al. 2009). User habits, concerns, and expectations that occur due to prior experience or inexperience have an impact on their actual interactions. Thus, pre-usage experiences are as important as usage and post-usage. Considering recent usage experiences, it is beneficial in order to comprehend ongoing, immediate, fresh, and more clearly remembered experiences. Besides, in the post-usage stage, users' experiences might be divergent because users might possess different perceptions. Their evaluations might be different after passing through a number of stages and being able to observe previous periods differently (Karapanos et al. 2009; Roto et al. 2011). Thus, in our study, semi-structured interviews constituted the basis of the methodology throughout all three stages.

The first stage of the study was started after introducing the study and receiving the consent of the participants. Three scales—abbreviated Technology Readiness Index (TRI) (Parasuraman and Colby 2001), Satisfaction with Life Scale (SWLS) (Diener et al. 1985), and Scale of Positive and Negative Experience (SPANE) (Diener et al. 2009)—were employed to gather data about the participants' backgrounds, general well-being, and their status about using technology. This helped to create a frame attempting to differentiate pregnant women "types." Next, a semi-structured interview was conducted involving questions about daily pregnancy experiences, experiences with general mobile applications, experiences with

Application usage date:
Application usage time(s):
Below, please check the feature(s) which you have recently used. You can also note down how many times you have used the checked feature(s) on this day.

FEATURE / CONTENT	✓	FEATURE / CONTENT	✓
Pregnancy information (Baby development, bodily changes, etc.)		**Contraction timer/ tracker**	
Countdown/ Due date calculator		**Kick counter/ tracker**	
Pregnancy Management (Checklist,to-do list, reminder, notification, birth plan, etc.)		**Weight tracker**	
Diary/ Journal		**Exercise tracker**	
Forums/ Communities/ Clubs		**Nutrition tracker**	
Sharing (Facebook, Twitter, E-mail)		**Medication tracker**	
Baby names		**Sleep tracker**	
Store/ Shop		**Mood/ Emotion tracker**	

Other feature(s) (Please specify):

Fig. 5.2 Content of a feature checklist card

mobile health applications, and experiences with mobile pregnancy applications. Then, three application cards were presented, which demonstrated the features of three predetermined pregnancy applications with supportive snapshots taken from online app stores (iTunes Store or Google Play Store). Participants were asked to look over the applications and to select one to use for 6 weeks. They were then asked why they selected that particular application and what their expectations were from it. After the selection, the reasons for selection and expectations from the applications were asked. Feature checklist cards were provided for the next stage in which participants might note down the application features they would use, their interaction time, and interaction frequency (Fig. 5.2). There could be missing and inaccurate parts while reporting the experiences later on (Nielsen 2010), and the given interactions could be repetitive in the course of daily life. So, the researchers used personal notes, documents, and diaries in order to avoid these issues (Intille et al. 2003). Participants were given printed and digital alternatives of these cards that were more portable and user-friendly. For the print-out version, a participant was given several cards attached together with a key ring to use by carrying during the daily life.

Table 5.1 Summary of trimester-specific participant distribution

	Age range	First pregnancy	Multigravida	Total # of participants
First trimester	26–35 (*M* = 31.20, SD = 3.33)	9	1	10
Second trimester	25–40 (*M* = 31.08, SD = 3.94)	10	2	12
Third trimester	25–40 (*M* = 33.09, SD = 4.18)	6	5	11

After 6 weeks, additional semi-structured interviews were conducted to evaluate the user experience. Ideally, interviews were conducted face-to-face, but depending on the participants' locations, if required or demanded, interviews were also carried out via Skype. The participants were asked if they would like to use the applications further, how the applications would make them feel (better or happier), and what their suggestions were about the application and interaction quality to improve the pregnancy applications. Furthermore, two scales used in the first stage, SWLS and SPANE, were applied again to understand whether there was a change that occurred for the well-being of the participants. All of the interviews were voice-recorded for transcribing after the study.

5.3.2 Sample

Quota sampling was used by recruiting 10 pregnant women for each of the three pregnancy trimesters (30 pregnant women in total). The study was finalized with the participation of 33 pregnant women. However, two of the participants had early labor, and one of the participants did not give sufficient responses during the entire study. Thus they were removed, and three more participants were recruited. In parallel to the applications used in the study, participants used either iPhone (iOS operating system) or smartphone with Android operating system. Participants reported to have adequate English knowledge to interact with the selected applications. As the target user profile and sampling criteria already constituted a limitation on the prospective sample size, participants were also recruited according to availability and snowball sampling. The study had been announced via different channels, such as using pregnancy blogs, gynecology association, prenatal yoga centers, pregnancy education organizations, other non-pregnancy-related local organizations, social media, and social contacts. The ages of the participants ranged from 25 to 40. In addition, 25 out of 33 participants were first-time moms and 8 of them were multigravida. Additionally, 7 participants had doctoral degrees, 12 participants had master's degrees, 12 participants had bachelor's degrees, and 1 participant had an associate's degree. A summary of participant distribution based on trimesters, age range, and pregnancy numbers can be seen in Table 5.1.

5.3.3 Tracking

Pregnant women in each of the trimesters were tracked for approximately 6 weeks, although one trimester is roughly composed of 3 months. This decision was made since most women do not know they are pregnant, or do not want to announce it, until several weeks into the first trimester. It is also not efficient to continue a study in the third trimester because the pregnant women are so focused on their birth date that it is a burden for them to finalize the required tasks. In order to standardize the duration for each trimester, 6 weeks was found to be appropriate. During the entire 6-week tracking period, apart from prompts and messages, the participants were contacted biweekly for interviews. The decision to interview biweekly was made as the result of a pilot study. There were both 1-week and 2-week intervals in the pilot study. Weekly interviews were found to be too much for several reasons. Firstly, data started to repeat and became saturated. Secondly, too many interviews created extra responsibilities and burdens for the pregnant women. In addition, the participants found that there were not enough changes in 1 week to support weekly interviews.

5.3.4 Selection of Applications

Three smartphone applications were selected to be utilized in the study: *BabyBump Pregnancy Pro*, *Ovia Pregnancy Tracker*, and *My Pregnancy Today*. These applications had versions compatible with both iOS (iPhone) and Android operating systems. Although there were small differences among the interfaces for different operating systems, the overall interaction and content were almost identical.

Before deciding upon these three applications, a wide range of pregnancy applications had been examined. Examiners gathered the most up-to-date ratings of the applications in the application stores (Apple App Store for iOS operating system and Google Play Store for Android operating system) and the best pregnancy application reviews of popular technology and pregnancy websites. Among these, applications compatible with both iOS and Android operating systems were listed, and application numbers were reduced to 35. Subsequently, those applications were reexamined in detail considering their features and the related wellness dimensions that they could address and support. It was seen, no wonder, that almost all applications aimed at supporting physical wellness first, which was inherently accompanied by intellectual wellness to expand pregnancy-related knowledge. Nonetheless, when the applications addressed more than two wellness dimensions, they were incorporated herein. Figure 5.3 summarizes the selection criteria for all applications.

All three applications had upgraded versions, and these versions were utilized in the study in order to eliminate any problems that participants would encounter in the free versions. Also, the upgraded versions included more diverse features to help collect more insights. When the selected applications were not free, which were the *BabyBump Pregnancy Pro* applications for iOS and Android, participants were compensated with the required amount of money.

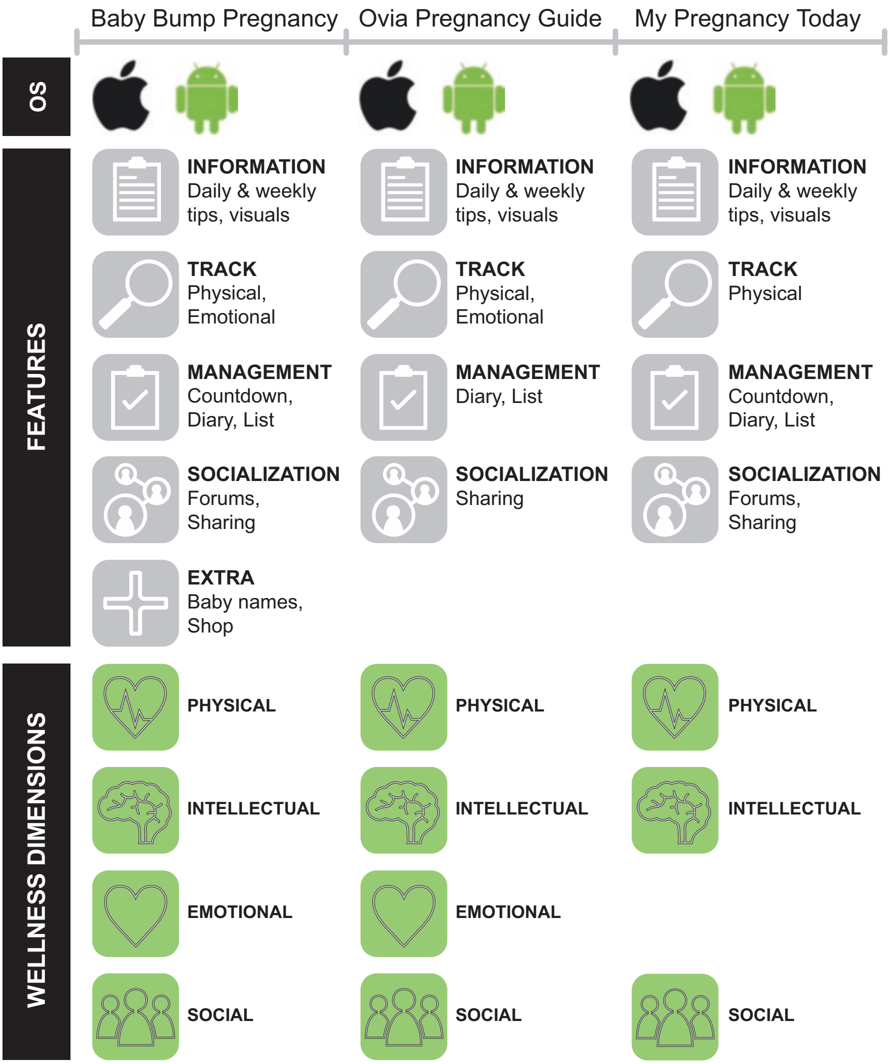

Fig. 5.3 Selection criteria for the applications

5.3.5 Data Analysis and Dimension Extraction

Data analysis started with the transcription of the voice-recorded interviews. As there were 33 participants and 4 interviews for each, approximately 132 interviews were transcribed into Microsoft Excel sheets. These qualitative raw data were analyzed with content analysis, a method to systematically analyze and code data in order to achieve coherent, valid, and replicable interpretations and inferences through high volumes of data (Krippendorf 2004; Bogdan and Biklen 2007). General scheme and inductive coding were used since there were no exact predetermined codes in the literature about positive user experiences and pregnancy-related experiences; yet, certain codes had been retrieved from the general user experience and HCI literature. Recurring patterns and meaningful segments in data were coded considering possibility-driven and positive experiences. These coded segments constituted the main positive user experience dimensions with mHealth technologies for pregnancy. Considering the new dimensions that were identified during the coding process, a "glossary of terms" table was created to ensure coherency and reliability in the assigned codes. At the end of this content analysis, 2220 statements and 3421 dimensions were identified. Statements addressed the participants' comments. The analysis was relational, and the dimensions were coded regarding the cause-effect relationship. In addition, not merely one-level conceptual analysis was performed; in fact, it was sought to go beyond individual dimensions toward multidimensional conceptual relations for avoiding to lose rich underlying meanings. 2402 dimensions were identified as in a mutual relationship (1201 affecting + 1201 affected), and 1019 stand-alone dimensions were identified without being in any cause-effect relation.

5.4 Positive User Experience Dimensions with mHealth Technologies for Pregnancy

Both data collection and data analysis procedures were multifaceted in order to gain and reveal rich user insights. In accordance with that, multiple dimensions were elicited which required sophisticated and multilateral approach for interpretation. In the following parts, findings and their interpretations were discussed together. Initially, elicited positive user experience dimensions and their multidimensional relations were demonstrated, which was highly crucial to monitor affecting and affected dimensions as a broad picture. Afterward, components of mHealth technologies for pregnancy were explained, which could be useful for designers and developers informing about certain aspects of the technologies. Then, dimensions were handled uncovering the needs and expectations of pregnant women in a temporal context, which was essential to support the wellness of pregnant women according to their daily life changes in different pregnancy trimesters.

5.4.1 Dimensions and Multidimensional Relationships

Major relationships among the dimensions were visualized by using the NodeXL open-source network analysis and demonstration tool (Smith et al. 2010). The resultant multidimensional map (Fig. 5.4) was noteworthy as it conveyed more

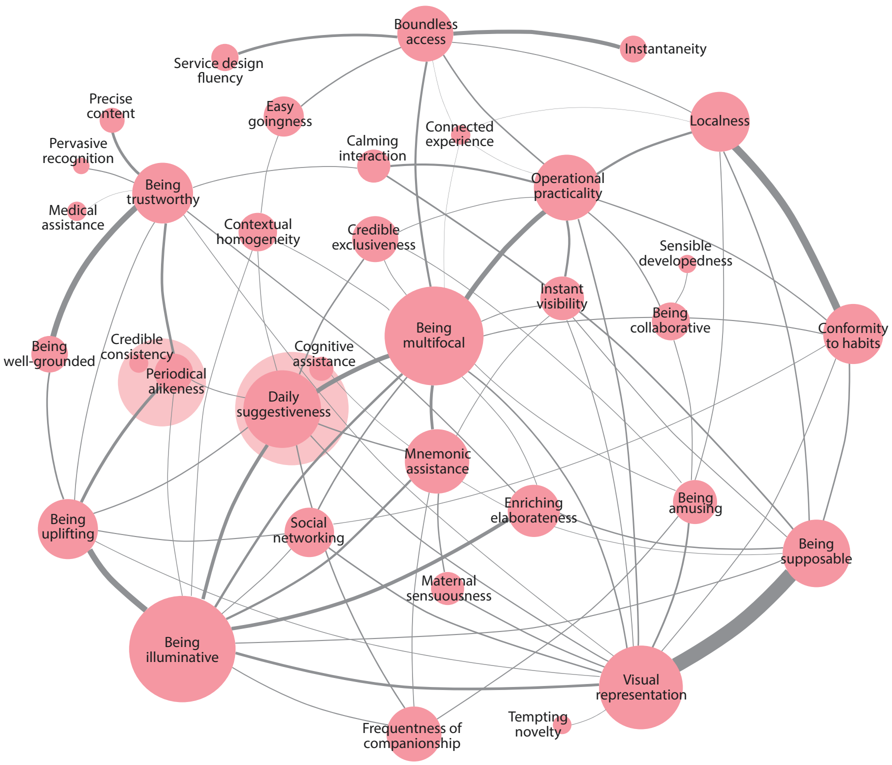

Fig. 5.4 NodeXL map demonstrating the relationships among the dimensions

than binary data (i.e., it reveals relationships of all dimensions with each other rather than dimensions in pairwise unidirectional or bidirectional cause-effect relationships). In Fig. 5.4, the sizes of the circles represented the related concepts' frequencies. In a fashion similar to this, the thickness of the lines represented the frequencies of the corresponding relationships and, so, the strength of the bond between dimensions. In addition to the multidimensional connections, those frequencies and relationships' strengths were guidelines to sensibly demonstrate the findings and to present apparent possibilities providing positive user experiences. The flow of the explanations below was organized with regard to the frequencies of the dimensions.

According to participants, *being illuminative* was the most crucial dimension involved in providing a positive user experience. Being illuminative was not only about the presence but also the enlightening quality of information provided by mobile pregnancy technologies. Thus, providing an illuminative experience carried those technologies beyond being simply informative; it was eye-opening, awareness raising, and revelatory. Though participants were in need of explanations regarding risky and harmless situations, they wanted illuminative information about diverse issues related to pregnancy and postpartum stages (individual changes, baby development, symptoms, nutrition, exercise, medication, drugs, shopping, etc.).

Being multifocal was highly significant for the participants. Having diversified foci promoted different possibilities for pregnant women, considering both the individual pregnant woman and multiple pregnant women as having unique pregnancy experiences. Being multifocal had more positive attributes than being multifunctional as it was more than providing many functions. It comprised diverse features and content in mobile pregnancy technologies with different focal points on the mother, baby, and other people such as father, who elicit sophistication and versatility for pregnant women and their daily lives. In addition, the followings were identified as multiple ways to make mobile health pregnancy technologies multifocal: not being merely baby- or mother-focused, offering extra features and content not existing in generic applications (such as tracking features, indexes, etc.), being able to conduct a certain task in different ways such as via either application or e-mail, and having language, display (scroll, full text, pages, video, e-mail, theme), note-taking (voice, text), filter (alphabetical, week-by-week, photo, personal vs. generic information), content (default vs. user-added), and unit of measurement alternatives.

Visual representation was also among the most frequently mentioned dimensions. Presentation of visuals, images, photos, graphics, and videos in application features was categorized under this dimension. Participants did not demand the number of visuals to support and enhance their experiences; in fact, they highlighted the significance of the suitability, quality, and quantity of the presented visuals. Sound visual narrative appeared important for concretizing and making all abstract, intangible, medical, and even sometimes worrisome information friendlier and pleasing.

Guidance of pregnant women in their daily life was classified as *daily suggestiveness*. Apart from solely receiving factual and descriptive information, a great number of the participants needed the content and features of mobile pregnancy technologies to guide them throughout and, even after, the pregnancy period. They expected suggestions and tips about general pregnancy problems and other possible issues in their daily lives. It was mentioned that those suggestions and tips could be used for a daily assistance service and prepare them to face diverse situations during and after pregnancy.

Being supposable was prominently covering both the comprehensibility and internalization of the provided features and content. In essence, comprehensibility was not sufficient for the participants to attain positive experiences. Participants needed to achieve easy and satisfactory interactions by comprehending, picturing, and internalizing the retrieved information. Interfaces, menu structures, and visualization and communication styles of mobile pregnancy technologies had a central role in enabling participants to match the provided information with themselves, which aided them to grasp the changes of themselves and their babies.

Another commonly mentioned dimension was *operational practicality*. Despite appearing as a pragmatic dimension, operational practicality was necessary to ease the pregnant women's actions and lives. Participants' remarks about being able to use mobile pregnancy technologies easily without any struggles and interacting with practical and convenient features and content which would decrease their effort and ease of their actions and life were categorized. Different from the conventional interpretation of practicality, operational practicality is identified to be parallel to pregnancy-long practicality. This implied a functional quality, indicative of not being obliged to learn new things for a definite and temporary period and being able to adapt quickly retrieved information into daily life easily.

Application features and content that helped to remind women with different requirements and also reminding to do things during pregnancy were observed to be popular. Participants also mentioned the evocativeness of pregnancy stages. In that regard, receiving notification and alerts and accessing to the right information in the right place were mentioned. Thus, warnings and reminders were stated to be highly important, notably considering “momnesia,” which was a temporary memory impairment during pregnancy period. “Momnesia” affected the daily actions of the participants, as well as the great number of things to be done during pregnancy. Therefore, *mnemonic assistance* eliminated or at least minimized the necessity to keep everything in mind. This potentially prevented severe health-related problems related to medication intake and critical medical procedures.

Being trustworthy was of great significance, especially since the point at issue was health. Trustworthy application and information would achieve the reassurance for many pregnancy concerns and worries.

One of the most important hedonic qualities was identified as the uplifting quality of the mobile pregnancy technologies. *Being uplifting* was highlighted excessively because pregnancy causes worries about the cases that were normally considered small issues in the regular lives of people. That demonstrated that the pregnancy changes not only the physical condition of the pregnant women but also the psychological state of them. Thus, participants needed mobile pregnancy technologies to provide a relief from their worries and concerns. They needed not only relieving and relaxing application features but also a calming language and expression style to feel uplifted. For instance, it was suggested that applications could emphasize the changes and symptoms in pregnancy that were experienced by the most women which were completely normal.

Localness was expressed considerably. This result was mainly because of the limitations of the study; as previously mentioned, mobile applications used in the study were in English concerning predetermined criteria. Nevertheless, the localness dimension did not show up only in regard to the foreign language. Although all of the participants possessed English knowledge, incorporating country, city, and culture-specific features and information were requested to identify local qualities. To illustrate, information about pregnancy courses in a certain city, country-specific food suggestions, local baby names, and culture-specific pregnancy procedures were requested. This might have foreshadowed the vitality of feasible mobile pregnancy technologies in the local context in order to foster the integration of those technologies into everyday life.

Compatibility of the provided application features with pregnant women’s habits and previous experiences was evaluated under *conformity to habits* dimension. This dimension revealed to be prominent when familiarity was the point in question, since the similar features to the previously encountered experiences influenced the current experiences. Mobile pregnancy technology features which influenced pregnant women's habits also prepared them for the novel and unfamiliar pregnancy period.

The *boundless access* dimension, which was about being able to access applications, application features, and content boundlessly, was also found significant. Participants highlighted that the advantage of the pregnancy applications was the ability to access necessary information and receive support whenever and wherever desired, as most pregnant women had been already following various pregnancy resources.

Frequentness of companionship meant as being a loyal companion by supplying information and interaction frequently. There was a disaccord about frequentness. Some participants noted that the applications should provide information, send notifications, and allow data input for weight daily rather than weekly or monthly, or they demanded belly photo shoot weekly rather than monthly. On the other hand, some participants, especially the experienced ones or even the ones toward the end of their first pregnancies, mentioned that less frequent information would be sufficient. Yet, it can be deduced that depending on the pregnancy conditions, personal issues, and weight gain patterns, the demand for frequent interaction with the applications could have changed.

The comments of participants about providing detailed, in-depth, and rich information were tackled under the *enriching elaborateness* dimension. Participants were usually not satisfied when applications provided generalized and summary information. This was mostly due to the fact that they had been reading other resources concurrently. Therefore, they needed mHealth technologies to add something more or new to the information that have already been provided.

Credible exclusiveness was another considerably asserted dimension, particularly because each and every pregnancy was unique. Participants needed customizable interface, features, and content. This would allow users to enter personal data and track them. Furthermore, giving personal information and suggestions would appear as important application features. However, credible exclusiveness was more than providing personalization and customization; it was way more significant for the participants to feel exclusive in order to have more trust in mHealth technologies.

When participants mentioned creating networks and communicating with other pregnant women, other people, and their spouses, they were categorized under *social networking*. This dimension showed up in both a direct and indirect nature. When the applications incorporated explicit and intentional features to bring about increased interaction between pregnant women and other people, these features were interpreted as direct social networking. Pregnancy forums, e-mail notifications, and tips sent to spouses were the direct features. On the other hand, certain visuals and pregnancy information showed up as indirect feature to demonstrate, explain, and share the pregnancy period. In those cases, pregnant women shared those visuals and information with others which had not been actually targeted for them. In other words, indirect social networking involved other people who were not intended and targeted in application features, yet which had a part in communication.

For instance, when participants took the snapshot of a visual or information on applications and sent them to their husbands, or when they were sitting and chatting with their friends and opened the applications and showed certain content to their friends, they were coded as indirect social networking.

Though discussed plenty of times, there was no consensus on the *being amusing* dimension. Some participants requested entertaining and amusing application features and content because receiving just the information seemed boring and ordinary to them. They reported that incorporating humor to the content would make mobile pregnancy technologies more distinct from other pregnancy resources like books, websites, and pregnancy blogs. Other pregnant women were merely function-focused and goal-focused, so the entertaining qualities of the applications were not critical to them.

Not the majority, but several participants mentioned the following dimensions. *Instant visibility* was related to the statements of participants when they were or were not able to see certain application features, menus, and content without losing time. Not only the existence of demanded features but also the instant visibility of them was stated as significant in order to easily notice, find, and use the required content. To illustrate, when the content remained out of sight due to gigantic visuals or due to inconsistent hidden menus, participants hardly recognized or reached their target. The *easygoingness* dimension referred to features which provided conformable, compliant, and formative interaction while the user was accessing, editing, or navigating through application content. Examples included being able to follow the desired pregnancy week; being able to modify, edit, upload, mark, or delete information; and being allowed to write or do desired actions in a comfortable way. Though having a desired quality, this dimension occasionally led to a decrease in application use because participants were able to benefit from it at a single time by reading all the successive contents. *Periodical alikeness* was about the parallel progression of the pregnancy changes and symptoms with the provided information. Participants underlined the importance of parallel information with the actual pregnancy week because of both counting on the information and understanding the suggestions in the pregnancy week or period. *Being collaborative* dimension consisted of statements when participants did not use the applications passively. In fact, they demanded interactive features and content, permitting user input and track rather than solely receiving information. Furthermore, pop-up notifications, e-mails, and such interaction styles were also mentioned as enablers of collaborative use. As it was mentioned by several participants, c*ontextual homogeneity* appeared mostly as an undesired issue. As information overload occasionally occurred due to following diverse information resources such as the Internet, books, pregnancy websites, and blogs, participants found most of the contents homogenous and similar in those diverse resources. Hence, repetition and prevalence of content were questioned by the participants, and eventually, heterogeneity was demanded from mobile pregnancy technologies.

Certain dimensions received lesser emphasis than the prior ones, yet they were identified as important for the participants. Grounding information on scientific resources, medical professionals, theoretical information, and encyclopedic information were evaluated under the *being well-grounded* dimension. It was important to note that, at this point, this dimension was slightly different from the medical assistance dimension, yet, it appeared to have cause and effect relationship in some cases. Even though being informed by specialists and doctors can be related to medical assistance or being well-grounded, it does not necessarily be a dynamic conversation or communication hereby. This dimension was actually more content focused rather than interaction focused. *Maternal sensuousness* was perceived as emotional and romantic by the participants. Especially, addressing the sense of motherhood and maternity feelings, in addition to having feminine appearance and content, was found pleasant by some of the participants. However, there were also participants who did not want such qualities. The ones who did not want emotional qualities asserted that they needed to see rational, pragmatic, and functional qualities and found emotional qualities tacky and antipathetic. Qualities related to maternal sensuousness can be exemplified by mood tracking, receiving notifications from baby's mouth or with baby cries, and having pregnancy journals. *Calming interaction* emerged as another dimension for facilitating and relieving interaction. Having a simple, plain, and clean interface and features and not incorporating any complexity causing dissatisfaction or trouble were noted. In order to feel calm, participants majorly suggested categorizations and logical flow of information with suitable visuals. *Service design fluency* was about issues and problems about the flow of service design. Though technical issues that affected service design fluency were not of vital importance to participants, they were related to receiving diverse services without having any obstacles in any steps.

Assertion amount of some dimensions was not eye-catching; however, they were stated as qualities that made a difference among other technologies in a positive way. When participants have talked about precise, accurate, and pure information and experiences, those statements were included in *precise content* dimension. Not having infollution and not conveying nonsense information were important. *Instantaneity* (the ability to carry and use mHealth technologies wherever one desired) was interpreted as an advantageous issue considering other pregnancy resources because when questions came to participants' mind (and when they were worried about certain pregnancy issues), they needed to consult to an information source. *Cognitive assistance* was also expected in order to facilitate interaction and to use the applications efficiently. More clearly, this dimension was about directing users while using application features and content. A couple of suggestions were outlined in that regard: a step-by-step demonstration of the necessary information; provision of links directing users to other features, content, or websites; and the demonstration of tutorials after signing up and before beginning to use the applications. *The connected experience* was indicated as the suggestions to improve pregnancy applications in general. Those participants needed to feel connected to other devices, healthcare products, scales, applications, and stakeholders. *Tempting novelty* was recommended as the encapsulation of unprecedented effective features and presentation styles and provision of a novel technology and interaction, and thus not being conventional and classical. Different from the tempting novelty dimension, participants expressed their perception about the applications' advanced look.

Thus, *sensible developedness* could be an issue to consider to convey a positive impression. The *medical assistance* dimension, as briefly mentioned, was about having contact with a doctor and being able to ask questions in a synchronous or asynchronous manner. A few of the participants demanded to be able to call a doctor or send a SMS or e-mail, when they needed to learn something, and relieve their worries. They suggested that this could be their personal doctor or any one of multiple doctors, each of which could have different patients and pregnancy groups. *The credible consistency* of application features and content was addressed by a few participants. To realize this dimension, participants suggested using the same visual or expression style and maintaining similar interaction styles for similar functions and menus. The least mentioned dimension was *pervasive recognition*, which was about being a preferable, known, and recommended application. The incorporation of other people's comments affected the perception of the applications as popular and reliable, which could serve as a justification to continue to use the applications. This provided a very quick and brief overview of the study results of the major dimensions to consider while designing pregnancy applications, as well as showing how to foster integration of them into the daily lives of pregnant women. Besides these dimensions, the membership and payment requirements of the applications were discussed by a few people. However, they were not included in the analysis due to their assertion amounts and their scope.

5.4.2 Components of mHealth Technologies

In this section, positive user experience dimensions with mHealth technologies for pregnancy were analyzed considering the related components of the technologies. Components which took part in those experiences were mainly the content, interaction, appearance, and function. Figure 5.5 presented the distribution of positive user experience dimensions among each component considering the number of statements.

Regarding the component names, *content* was the contextual and informative qualities. Contextual qualities were the most frequently mentioned features. There were 1388 dimensions related to contextual needs, expectations, and suggestions. Meaningful and informative feedbacks about the topics such as nutrition, exercise, pharmaceuticals, pregnancy changes, symptoms, baby development, shopping, and fraternal relationships were expected. It was observed that these qualities were not solely about the subject of the content; rather how the information being transferred and understood was also had great significance. As given in Fig. 5.5, providing daily suggestions, being local, being uplifting, being trustworthy, and enriching elaborateness were highly significant dimensions in providing satisfaction with the application content.

Interaction was about the qualities and experiences regarding how pregnant women interacted with the applications and technologies. Interaction-related statements

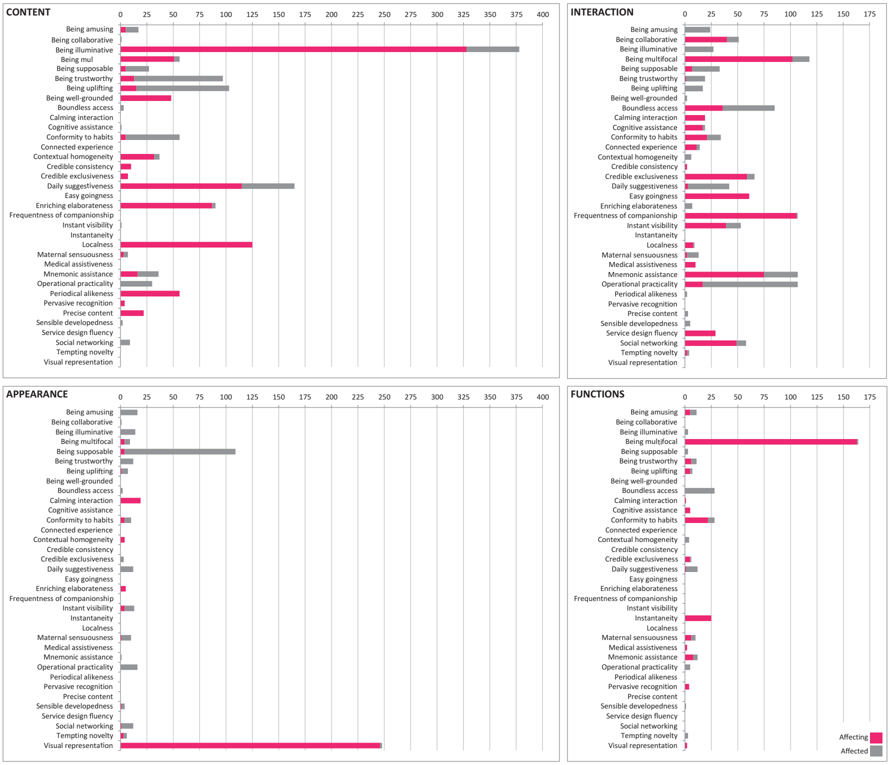

Fig. 5.5 Distribution of dimensions among the component

were highly observed during the study. 1153 concerns were reported about how pregnant users used the application functions, menus, and content and how they navigated through all these qualities. In that regard, being multifocal, frequentness of companionship, mnemonic assistance, and operational practicality dimensions should be taken into consideration for having pleasing interactions.

Appearance was about the application or technological qualities related to the visual appearance. Out of all dimensions, 533 of them were related to appearance. The presence or absence, quality, and appropriateness of the visuals were considered in identifying visual appeal. Dominantly, visual representation dimension and being supposable dimension were main consideration points for visual appearance.

Function was about the presence/absence of certain or multitudinous functions, their capabilities, and potentials. 347 dimensions were directly about the functions. Being multifocal dimension received the greatest attention from the participants in regard to the functions of the mHealth applications. In that regard, boundless access, conformity to habits, and instantaneity were other leading dimensions which help to develop more satisfactory functions.

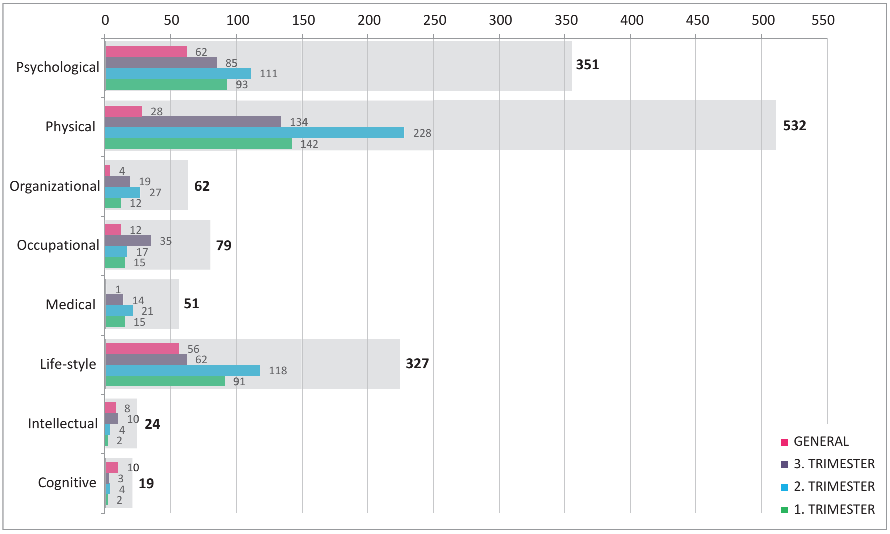

Fig. 5.6 Changes during pregnancy

5.4.3 Temporal Needs and Expectations

It was observed that expectations about these dimensions and related components and qualities changed depending on different pregnancy trimesters and pregnant women types. Hence, participants' comments about changes and expectations in different pregnancy trimesters were analyzed and coded with another content analysis. As a result, eight main categories emerged as cognitive, intellectual, lifestyle, medical, occupational, organizational, physical, and psychological changes. Most of the changes were interrelated with a cause-effect relationship. So, it can be argued that changes during pregnancy are also multidimensional. Figure 5.6 presented the total number of statements (affecting change and affected change) for each type of changes in each trimester. Those categories can address qualities of wellness during pregnancy, and they can give hints about the qualities of mHealth technologies to support wellness during pregnancy.

Cognitive changes were about the changes in mental functioning and performance. For instance, impairments in memory, perception, concentration, and comprehension were observed during pregnancy. Several participants expressed that they started to forget even the most frequent and familiar things that they had done in their daily lives, which then affected their daily lives, work lives, social relationships, self-perceptions, feelings, etc. They were then in need of cognitive support before encountering or when encountered with related problems. Considering mHealth technologies, cognitive assistance, daily suggestiveness, mnemonic assistance, easygoingness, instant visibility, and operational practicality were some of the prominent dimensions that can support such cognitive changes.

Intellectual changes pertained to the alterations in knowledge, consciousness, and awareness. Commonly there were differences between first pregnancies and subsequent pregnancies, and apparent changes occurred between the first trimester and the later ones. However, even though knowledge was accumulated in the subsequent pregnancies and toward the end of each pregnancy, participants still felt unready and insufficient considering what they had learned. Even though they had learned many things as they are getting closer to the birth, they were in need of different information in each time period. In the first trimester, they were more interested in information about pregnancy symptoms and dos and don'ts, whereas, in the second trimester, they were interested in information about management, shopping, and organizational issues. In the last trimester, they were in search of information about the birth and postpartum periods. Expecting women who had other children were concerned with issues related to siblings. Considering these observations, it can be argued that mHealth technologies can promote intellectual changes. To actualize this, positive user experience dimensions such as being illuminative, being uplifting, enriching elaborateness, being well-grounded, and daily suggestiveness may play a critical role.

Lifestyle changes involved changes in lifestyle habits, behaviors, routines, preferences, and responsibilities on diversified issues, such as diet, exercise, traveling, responsibility sharing, social interaction, and flow of life. Those changes were usually in parallel to the other trimester-specific changes. For example, due to physical changes like nausea and acid indigestion in the first trimester, some participants changed dietary habits. Thus, they needed support considering both physical changes and related lifestyle changes. Another example was in the last trimester, as the pregnant women's life tempo slowed down because of increasing belly growth and weight gain. This negatively affected their psychology as they felt less able to do things independently. In order to facilitate pregnancy through different lifestyle changes, mHealth technologies should consider positive user experience dimensions like being multifocal, being illuminative, daily suggestiveness, localness, and conformity to habits.

Medical changes are related to the participants' statements such as doctor controls, medical treatments, results of medical examinations, and analysis. It also included some routine medical controls as these affected their life, routines, and feelings. Examples of positive user experience dimensions to support pregnant women were being well-grounded, being trustworthy, periodical alikeness, being illuminative, enriching elaborateness, localness, being collaborative, connected experience, and boundless access.

Occupational changes emerged regarding work performance, attendance, and continuity. Physical changes affected their work performance most notably in the first trimester. Some of the participants were on maternity leave in the last trimester and reported certain changes due to ceasing working. Apart from these, most of the participants complained about not being able to take care of organizational issues and shopping due to working. In order to support pregnant women throughout occupational changes, the cognitive and mnemonic assistance, being illuminative, and being collaborative dimensions can be taken into consideration in mHealth design.

Organizational changes were about organization, preparation, and management related to pregnancy, birth, and postpartum periods. Most organizational changes occurred during the second and third trimesters. According to the participants, starting preparations were more reasonable after the riskiest period—the first trimester—had passed. They needed to make spatial changes at home and buy furniture and clothes for the children in the second trimester. Hospital procedures, preparation for the hospital, and maternal leave preparations were completed mostly in the third semester. Some arrangements could only be done once the women had started their maternity leave. In both the second and third trimesters, mothers needed to shop for maternity clothing and other specific items related to pregnancy due to increasing belly size and formation of edema in feet. To facilitate organizational experiences, the being illuminative, mnemonic assistance, localness, conformity to habits, and social networking dimensions were identified to be highly helpful.

Physical changes were the most frequently mentioned ones both in the literature and by the participants, as they were the most explicit and direct. It was apparent that physical changes for both mother and baby require medical attention and monitoring. In that regard, participants explained that physical changes generally triggered other changes in their lives. So, investigating changes holistically in cause-effect relationship and in the daily life context provides more meaningful and rich information, which could be used for better supporting wellness in pregnancy. There were many dimensions that should be considered in supporting physical wellness, such as periodical alikeness, being illuminative, daily suggestiveness, medical assistance, instantaneity, boundless access, frequentness of companionship, connected experience, being supposable, and being trustworthy.

Psychological changes were about the changes in affective and emotional situations. Participants elicited diverse emotions due to their daily experiences during pregnancy. It was reported that they occasionally felt concerned as their life started to change irrevocably in distinct ways. In addition, trimester-specific, weekly, and even daily changes have been reported. They may have associated emotional fluctuations with hormonal changes or other unidentified changes. Generally, the mothers were in need of emotional support considering their concerns and feelings. Positive user experience dimensions that were supportive of psychological changes were identified as being uplifting, calming interaction, maternal sensuousness, social networking, and being amusing.

5.5 Conclusion

It was revealed that new approach for mHealth applications that would support the wellness and well-being of pregnant women holistically and positively was necessary. It would, in return, enable the effective integration of mobile pregnancy applications into the daily lives of pregnant women. In other words, mHealth applications and technologies should not be merely providing information, helping decision-making, or providing solutions; rather, they should go beyond that by making pregnant women feel better and enhancing their wellness holistically.

Different pregnant women types and pregnancy trimesters addressed different possibilities. Not surprisingly, many mHealth applications in the market can offer personalized features. Nonetheless, this study showed that the most significant design implication was not superficially about personalization. Deeper and richer meanings behind the positive user experience dimensions and their mutual relationships should be considered while developing mobile pregnancy applications. Moreover, considering complex and multiple changes in the daily lives of pregnant women was highly crucial while designing highly supportive application content, interaction design, appearance, and functions. A suitable match between application components and positive user experience dimensions during different pregnancy trimesters (and for different pregnant women types) was required to provide more satisfactory and happy user experiences.

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Chapter 6
Utilizing mHealth Applications in Emergency Medical Services of Turkey

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6.1 Introduction

An indispensable part of healthcare systems is emergency medical services (EMS), which aims to provide care for serious situations in a timely manner to reduce morbidity and mortality. Because minutes or even seconds are critical in emerging situations, effective utilization and implementation of technology have fundamental importance for both emergency service providers and patients. Mobile health, abbreviated as mHealth, refers to strengthening public health services via the use of mobile devices and technologies, such as mobile and smartphones, tablet computers, personal digital assistants (PDAs), wireless technologies, and many others. The main advantages of mHealth applications are improving the effectiveness of EMS, facilitating access to emergency care, offering an opportunity to increase the quality of interventions, and thus assisting in saving lives. In other words, the implementation of mHealth promises enhancements both in the distribution of healthcare and access to it by means of increased availability of information and improved communication.

mHealth provides innovative solutions in the health industry, due to the increased computing power of mobile tools, in conjunction with developments in sensing and wireless technology (Pattichis et al. 2007). It also includes the ability to convert mobile devices into private laboratories with the potential to evaluate users' physiology, behavior, and environmental conditions (Kumar et al. 2013). mHealth has great potential to promote health communications to achieve healthier lifestyles, improve decision-making by health professionals and patients, enhance healthcare

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E. Sezgin et al. (eds.), *Current and Emerging mHealth Technologies*,
https://doi.org/10.1007/978-3-319-73135-3_6

quality by improving access to medical and health information, and facilitate instantaneous communication. Given its great potential, the subject of mHealth in EMS is an expanding area of research as well as managerial and governmental practices.

However, especially for developing countries, implementation of mHealth devices to the healthcare industry is particularly relevant, although most industries have experienced a significant change due to the development of such devices and systems (Lewis et al. 2012; Mechael 2009). The conversion of paper-based medical records into electronic records was the first stage, which took place in the early 2000s, in the process which eventually leads to mHealth (Tezcan 2016). Thus, due to the progressive nature of the process, dramatic benefits cannot be clearly observed, while different barriers remain a challenge for mHealth systems (Fiordelli et al. 2013).

The purpose of this chapter is to present a deeper understanding and a more detailed knowledge of mHealth utilization in the domain of EMS in Turkey. EMS is categorized into two groups: prehospital and hospital care services. The first group covers prehospital emergency care services, which deal with primary medical care given to a patient by a prehospital medical rescue team before the patient arrives at a medical facility. The second group covers the emergency departments of hospitals. For both groups, users are categorized as medical and nonmedical users. In each stage, mHealth devices, tools, or applications commonly used by each type of user are discussed in detail. Since the industry is still emerging, users confront different challenges, causing difficulties in the utilization of these advances. The various barriers against mHealth in Turkey are discussed, and some recommendations are presented.

To sum up, the organization of this chapter is as follows. Section 6.2 reviews relevant literature on mHealth. Section 6.3 reports the methodology. Section 6.4 presents information on mHealth utilization in prehospital emergency care services from medical and nonmedical users' viewpoints. Section 6.5 provides a discussion for hospital emergency care services in a similar way. Section 6.6 discusses main barriers and presents possible solutions. Lastly, Sect. 6.7 gives concluding remarks.

6.2 Background

After the 1990s, mHealth systems experienced enormous advances and became an important research focus. Thus, researchers present different definitions. Waegemann (2016) defines mHealth as an indicator of rising communication-based healthcare and an enabler of participatory health. In his report, Tezcan (2016) presented a detailed definition of mHealth. He stated that mHealth is an efficient method of collecting data and monitoring the health conditions of patients to ensure more rapid and effective treatment, as well as improving public health. Although significant technological advances have occurred in the last decade and mobility is the key to these improvements in many different sectors, mHealth is one of the more recent, and therefore, less developed types of mobile services available. Thus, its dynamics, applications, and impact are yet to be evaluated. Finland can be considered as the birthplace of mHealth industry, starting from the early 2000s (Kratzman 2013). Globally, in the twenty-first century, the mHealth market has expanded significantly. Kalorama Information (2013) indicated that telemedicine revenues grew by 237% between 2008 and 2013. Nuance Communication (2013) reported that as the social media environment maturates, there will be more frequent, more convenient, and more reliable connections between patients, between patient and doctor or any service provider, and between service providers, which also increases the utilization of mHealth. According to the World Health Organization (WHO) (2011) global report, almost 17% of countries have reported no initiative on mHealth adaptation, while 83% have reported at least one initiative, 70% have reported 1–9 initiatives, and 30%, at least 10. Unfortunately, impacts of many of these initiatives have not yet been measured.

Many researchers discuss possible advantages and usefulness of these mHealth projects and applications (i.e., Friederici et al. 2012; Hoyt and Yoshihashi 2014; Kaplan 2006; Mechael 2009). The main contribution of these generated projects and applications are considered to be:

- Improving access to healthcare
- Improving access to medical records
- Improving access to theoretical health information
- Improving aptitudes in diagnosis and treatment
- Increasing quality of healthcare
- Improving medical education and training
- Providing timelier service

Mobile information technology healthcare applications have been applied in many different countries (Wu et al. 2007; Haux 2006). Different wireless technologies, wireless networks, global positioning system (GPS), and cloud computing have been applied in various areas, including emergency health (Duis and Werken 2003; Pattichis et al. 2007). One of the most widely used tools is mobile or smartphone (Doganyigit and Yilmaz 2015; Luxton et al. 2011). The main advantage of this technology is to be personal, intelligent, connected, and readily accessible (Fiordelli et al. 2013; Nilsen et al. 2012; Steinhubl et al. 2013; Whittaker et al. 2012). Another global mHealth application is the use of SMS for different reasons, such as reminders of appointments, advising patients, and sending test results (Atun et al. 2006; Gurman et al. 2012). Personal digital assistants (PDAs) or, namely, handheld computers are also widely used tools in healthcare (Brilla and Wartenber 2004; Duncan and Shabot 2000; Khan Abu et al. 2007; Lu et al. 2005). Other mobile tools which are currently either in use or in development for mHealth applications are laptops, desktop computers, and wearable devices, such as smart watches, smart glasses, smart lenses, and sensor rings. The current focus is smartphone applications. According to the report generated by Research2Guidance in 2014, currently, there are more than 100,000 health- and fitness-related applications. In Table 6.1, different healthcare-related smartphone applications are listed.

Table 6.1 Smartphone application categories on mHealth

Categories	Smartphone applications
Based on medical specialty	Emergency medicine, forensic medicine, family practice, allergy, immunology, alternative medicine, anesthesiology, addictions, infectious disease, surgery, dermatology, endocrinology, disability, pharmacology, physical medicine and rehabilitation, gastroenterology, genetics, geriatrics, pulmonology, public health, hematology, internal medicine, gynecology, cardiology, occupational diseases, nephrology, neurology, odontology, audiology, oncology, orthopedics, pediatrics, plastic surgery, psychiatry, radiology, rheumatology, palliative care, traumatology, urology, intensive care, fitness
Based on field of interest	Emergency action systems, medical scientific literature, biotech, doctoral associations, education, residential care organizations, financial resources, national and global public health policies, visualization centers, GSM operators, hospitals, patient associations, patient communities, nonprofit organizations, privacy and security, mobile health and mobile health solutions, medical consultancy, medical suppliers, symptoms and diagnosis, application and software development, long-term care, data collection, health information systems
Based on operating system	Android, iOS, BlackBerry, Windows

Throughout 2014, an average of 300 smartphone applications, with a concentration on emergency medicine, was available in the Apple Store (Lin et al. 2014). Some of these applications were designed for nonmedical users or medical users, and others were designed for both groups. Applications for nonmedical user support routine activities such as calorie measurement, counting steps, measuring pulse, tracking drug consumption, reminders for drinking, and detecting signs of dangerous medical conditions. Applications for medical users have many different goals, including retrieving data (Metelman and Metelman 2016), calculating medical scores (Barnes et al. 2014), allocating patients (Yamada et al. 2015), and medical education (Kho et al. 2006; McAlearney et al. 2004; Menon et al. 2004).

Although mHealth is frequently considered as a system which functions with the interactive participation of patients and doctors, the target population of users includes many other individuals and institutions. Indeed, consumers of mHealth are not just patients but also family members as well as healthy people who need to monitor and preserve their well-being. mHealth is used by doctors as well as many other health service providers (i.e., ambulance staff, laboratory technicians). From institutional viewpoint, mHealth is not only needed by hospitals but also governmental and nongovernmental organizations, ambulance services, pharmacies, nursing and rehabilitation centers, medical call centers, medical companies, and health insurance companies.

In Turkey, mHealth has not yet matured, so applications have not reached to a satisfactory level. Currently, the Ministry of Health and some municipalities are in the process of making improvements and focus on health problems of the community and their solutions at national and local levels.

The Turkish Ministry of Health emphasized the need for progress in mHealth in the 2013–2017 strategic plan. In this strategic plan, which was presented by the

Ministry of Health in 2012, the necessity of the development and sustainability of mHealth systems; the spread of telemedicine, telehealth, and residential care; and the individualization of health are explicitly stated. In order to realize these priorities, "personalized mHealth" applications began in 2014. In addition, the following applications have been further improved, which have been in use for the last 5 years: "Centralized Doctor Appointment System," "The Pharmaceutical Track & Trace System," "Electronic Record Management System," and "e-Nabiz" system.

Currently, the level of mHealth activities and their integration into the health services are increasing both in developed and developing countries. Although these applications show a clearly rising trend, the utilization and evaluation rates are still relatively low due to different factors.

According to WHO (2011) report, main barriers against mHealth implementation are categorized as priorities, knowledge, policy, cost-effectiveness, legal issues, operation costs, demand, technical expertise, and infrastructure. The greatest barrier is cited as priorities, with an average level of 53% for all countries. The next highest rated is a lack of knowledge, with 47%, and the least cited is weak infrastructure, 26%. Indeed, particularly for developing countries, acceptance of mHealth by end user and healthcare providers is itself a challenge, because in reality, applying technology itself is insurmountable.

6.3 Methodology

In this exploratory study, observation and interviews were used to collect data. In order to understand basic mHealth tools and functions which are currently in use in prehospital emergency care, interviews were respectively carried out with a system administrator of 112 ambulance services of Izmir, a responsible member of Command and Control Center (CCC), and a paramedic in an ambulance team. To gather data on basic mHealth tools and functions used in emergency departments, responsible doctors of two different hospitals, Izmir Bozyaka Research and Training Hospital and Izmir Karşiyaka State Hospital, were interviewed. Each interview took almost 30–45 min. Additionally, the processes in CCC of 112 ambulance services and emergency departments of these two hospitals were observed. Each observation took almost 8 working hours. Data were collected between December 2014 and July 2015. All verbally collected data has been analyzed by using content analysis. Findings are presented as a step-by-step process in this chapter.

6.4 mHealth in Prehospital Emergency Care

Out-of-hospital emergent situations contribute enormously to morbidity and mortality. According to WHO (2014) report, ischemic heart disease and stroke are two leading causes of death. Trauma, myocardial infarction, and acute cerebrovascular diseases are also common causes of death. Since timing is so critical under such circumstances, early intervention would significantly decrease morbidity and mortality rates (Steg et al. 2012; Moroz and Spiegel 2014). Therefore, it is important to have efficiently designed and managed prehospital emergency care services. In their review paper, Hubert et al. (2014) highlighted the applicability and value of mHealth in prehospital emergency care.

According to government statistics reported by Turkish Statistical Institute, the causes of death in 2016 are as follows: 39.8% resulted from circulatory system diseases, 19.7% from benign and malignant tumors, 11.9% from respiratory system diseases, and the remaining 28.6% mainly from endocrine, nutritional or metabolic diseases, nervous system or sense organ diseases, external injuries, poisoning, and a few of others. Of the circulatory system disease deaths, 40.5% are due to ischemic heart disease and 23.6% due to acute cerebrovascular disease. Additionally, 34.5% of the deaths from circulatory system diseases are patients aged 75–84. Thus, saving time for such causes can make an improvement of public health in Turkey.

In their research, Sariyer and Ataman (2015) reviewed the prehospital emergency medical literature in Turkey, revealing the current status of these services. These services are composed of different parts, each with its own user. The process flow is summarized in Fig. 6.1.

As presented in Fig. 6.1, in Turkey, emergency calls are made via a call number, 112. Depending on the closest base station, the call is automatically directed to the appropriate city. In each city, there is a local prehospital emergency care service center, called 112 Command and Control Center (CCC). For instance, the local center (CCC) in Izmir, a major city, is located in one district, Narlidere. Thus, an emergency call made from any district of Izmir is directed there. The specially trained call center staff answers the call, and by following a scientifically generated protocol, she understands the emergency situation, finds the closest available ambulance to the emergency event location, and sends a prompt to this ambulance (Sariyer et al. 2016). After receiving the prompt, the ambulance, equipped with a team of paramedics, emergency medical technicians, driver, doctors in some cases, and a full set of prehospital emergency care equipment, is directed to the emergency event location to provide prehospital care. As soon as the ambulance team reaches the location, they make necessary first intervention to stabilize the patient, who is then transported to a hospital with an emergency department. Thus, in this process, which involves numerous steps, any technological advance which reduces the time taken to reach a hospital is crucial.

6.4.1 Utilization by Medical User

Medical users who are generally involved in prehospital emergency care services are responsible doctors, technicians, paramedics, call center staffs, ambulance drivers, and system managers. These users can be combined into three main groups: system administrators, CCC (call centers, responsible doctors), and ambulance

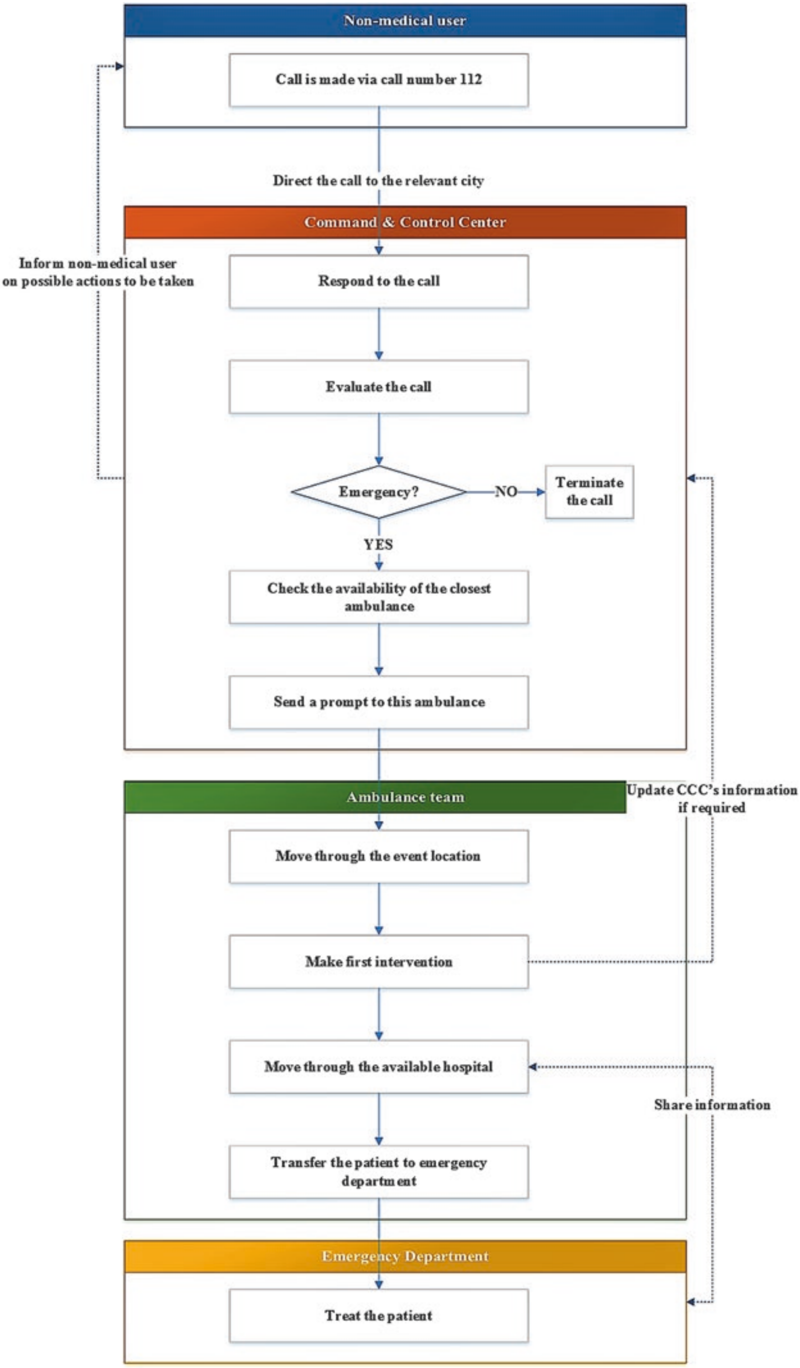

Fig. 6.1 Process flow chart of EMS in Turkey

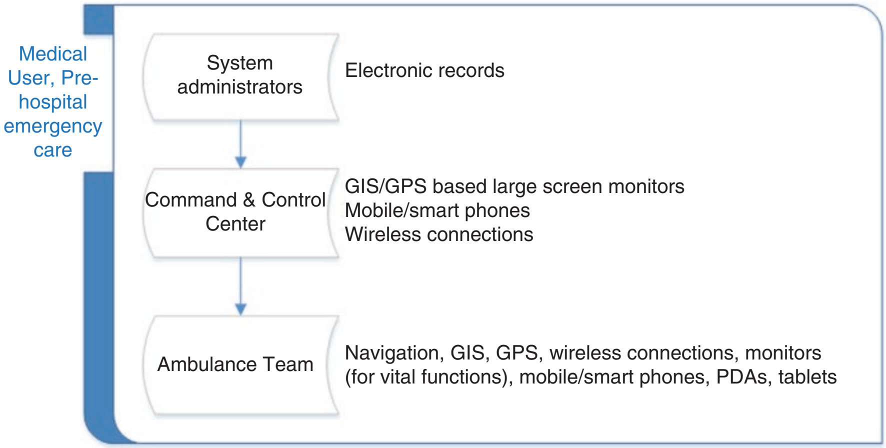

Fig. 6.2 mHealth utilization in prehospital emergency care by medical users

team (technicians, paramedics, ambulance driver). Although the implementation of mHealth applications is very recent, in both theory and practice, different mHealth tools and applications are currently utilized by users who integrate these applications into the system. The summary of mHealth utilization by medical users for this group is represented in Fig. 6.2.

In the design of CCCs, system managers and administrators have large screen monitors which are integrated with geographic information system (GIS) and global positioning system (GPS). All the information from calls arriving at CCC is electronically recorded. This information includes patient information, time and location of the event, directed ambulance, response time, route of the ambulance, and emergency department to which the patient is transported. This is a very valuable mHealth advance for system administrators and managers, since it allows data to be managed efficiently. If this big data is properly analyzed and interpreted, improvement in operations management strategies will follow (Sariyer et al. 2016; Sariyer et al. 2017).

CCC call center staffs also utilize mHealth applications. Large screen monitors clearly show the positions of available ambulances, as well as the information on the availability of hospitals' emergency departments. After answering a call of urgency, a staff member checks the availability of the nearest ambulances to the emergency location. Previously, ambulance availability could only be checked by phoning each ambulance team, causing a significant loss of time for such critical situations. A call center staff decides on which ambulance to direct and sends it a prompt. If the emergency location is sent verbally, time is lost. Thus, these locations are frequently sent by mobile devices such as smartphones. After a prompt is sent, the call center staff begin planning the optimal route to the hospital. Thus, while the ambulance is moving toward the location, the call center staff checks the availability of emergency departments. Here, availability means that an emergency department has resources required to treat the patient, is able to deal with the patient without any delay, and is near to the location. Additionally, for extraordinary circumstances, availability means a match between the requirements of the patient and the capacity of the hospital. Examples of such circumstances include extremity injuries requiring reimplantation; heart, brain, or other organ diseases requiring angiography; poisonings requiring antidote; poly-trauma patients; and patients requiring intensive care and ventilators. It is vitally necessary to transport these patients to hospitals with adequate medical equipment and practitioners in a time-efficient manner. In previous times, ambulances had to visit different hospitals until an available one was found. In some cases, the ambulance visited four or five hospitals until an available hospital was found. It was really a significant loss of time for patients in the ambulances and for other waiting patients. In contrast, call center staffs can now send relevant and vital information about patients and the expected arrival time of the ambulance to the available emergency department team. Therefore, they can be prepared in advance, which helps to reduce the time needed to treat patients.

mHealth tools and applications are also widely used by ambulance teams. When an ambulance team receives a command from CCC, the driver of the team immediately employs a navigation equipment based on wireless networks and global positioning system (GPS). This tool decreases the ambulance response time, since there is no need for the driver to find the location or ask others. On arrival, the patient is treated and transferred to the ambulance by paramedics and technicians. Ambulances are equipped with highly developed monitors, using wireless technologies. The patient is connected to this monitor to measure levels of vital functions, such as pulse, blood level, and blood pressure. If the paramedics or technicians are uncertain how to treat the patient, they send photos of the patient or monitor screen to the waiting emergency department team using their smartphones. Video calls can also be used in such situations. Furthermore, if ambulance paramedics and technicians are uncertain about treatment, they can also use mobile tools such as SMS texting, phone call, or video call with waiting hospital doctors or responsible doctors at the CCC. This communication may concern issues such as the type and dosage of a drug or, if the drug is not available, the suitability of available equivalent drugs. Mobile tools are also used to give information on the status of the patient to the waiting emergency department team. When the ambulance team reaches the event location, they can update the information originally given to the CCC. For instance, when the ambulance reaches to a patient suffering a chest pain, the ambulance team conducts an electrocardiogram (ECG) and sends it to CCC. If the responsible doctors at the CCC consider that a coronary angiography is required, CCC checks the availability of the emergency departments with angiography units and informs the ambulance team.

In addition to all these functions, CCC can use mobile devices in planning and managing patient transfers. If a patient needs to be transferred to another city, the CCC can determine the transfer type. Roads are generally used, but air or sea routes are also possible.

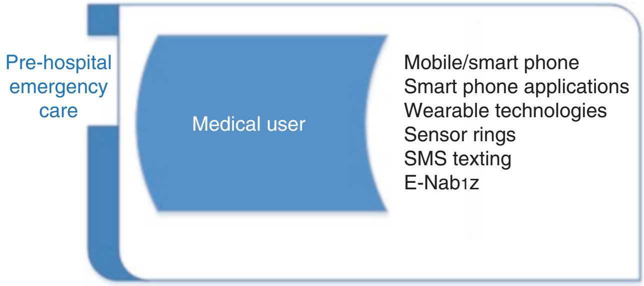

Fig. 6.3 mHealth utilization in prehospital emergency care by nonmedical users

6.4.2 Utilization by Nonmedical User

In prehospital emergency cases, nonmedical users can be patient's relatives, especially for chronic diseases, trauma, or stroke-based cases, or passersby who are at the scene of the emergency. In some cases, patients themselves can also be nonmedical users. Utilization of mHealth by nonmedical users in this group is summarized in Fig. 6.3.

A typical utilization of mHealth by nonmedical users in prehospital emergency cases is calling for a service. Currently, due to the widespread use of mobile phones, nonmedical users can call for an ambulance as soon as an event occurs. This is a major improvement; approximately 85% of the population in Turkey owns a mobile phone (International Telecommunication Union 2010). Calling an ambulance via mobile phone removes the need to search for a phone and sharply decreases the response time and the rate of mortality.

Different mobile applications exist for chronically ill patients. By using such applications, such a patient can assess his own condition to a certain extent and call for an ambulance if necessary. A diabetic alone at home can measure his blood glucose level using a stick blood glucose test and send the result to his doctor using mobile technologies, such as an SMS or e-mail. A patient with arrhythmia who feels irregularities in heart rhythm can use a mobile phone application to measure the ECG rhythm. The results can be sent from the phone placed on his chest directly to his doctor, who can then make a decision on the need for an ambulance.

Although less common, sensor rings are also used by some chronically ill or elderly patients. These sensor rings give a signal to a patient or a relative, and a demand can be made to prehospital emergency services without lost time. An example is a wearable technology for Alzheimer patients, who use technology such as GPS to show their locations.

Although some other projects are still under development, they will eventually be available for mHealth utilization by nonmedical users. One of these is video calls to nonmedical users to give necessary instructions on the possible actions before the ambulance arrives. Consider a pediatric case, in which an object is lodged the child's throat, restricting breathing. A video call can be used to show accompanying adults the steps of Heimlich maneuver before the ambulance arrives. Similarly, a video call to relatives of a heart-arrest patient can give basic life support instructions. Such early interventions will have a significant effect on saving lives.

6.5 mHealth in Emergency Departments

Emergency departments involve patients who arrive by an ambulance and others who come by their own means or with another person. In Turkey, emergency departments receive high volumes of visits, some of which are not real emergencies. Under this scenario, it is difficult for service providers such as doctors, nurses, consultants, medical assistants, secretaries, and administrators to increase the efficiency of emergency departments, provide service to emergency patients in a timely manner, and improve the quality of service. From patients' viewpoints, waiting for treatment is undesirable and negatively affects their well-being. The usage of mobile technologies is therefore considered as an effective solution for both medical and nonmedical users of emergency departments.

Basic mHealth tools and functions utilized by each type of users in emergency departments are represented in Fig. 6.4. As presented in Fig. 6.4, a nonmedical user initiates the process by applying a doctor for a treatment.

6.5.1 Utilization by Medical User

Medical users need unrestricted access to medical records at all times (Haux 2006; Wu et al. 2007; Johnson and Turley 2006). mHealth expedites access to and updating of medical records whenever and wherever required. In Turkey, many medical

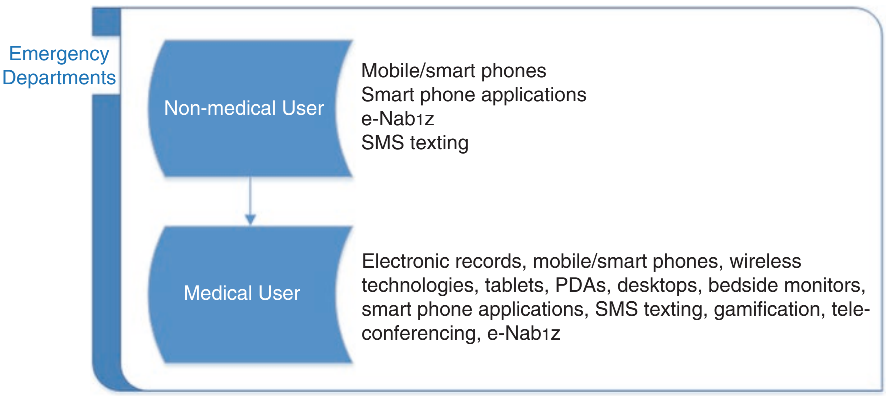

Fig. 6.4 mHealth utilization in emergency departments

users in different departments, including emergency medicine departments, use mobile applications to access data and enter new data into the system, by logging in with ID and password, which automatically generates the user's signature. PDAs or handheld computers with a wireless communication are frequently used for this purpose, but smartphones can also gain access to an electronic record system. All hospitals have at least one room dedicated to emergency department doctors, equipped with desktops.

Almost all hospitals, especially in urban areas, have bedside monitors in emergency departments, which facilitate treatments in such crowded environments. These monitors show vital signs, such as ECG rhythms, have pulse oximeters and many other functions, and give signals to warning of abnormal activity. Thus, a medical user can immediately intervene in such situations, or a doctor can be alerted by mobile applications by other medical users if outside the department.

As mentioned at the beginning of this section, many emergency department visits are by patients who are nonemergency cases. These cases generally take place at night. An obstetrics department patient may visit the emergency department if suffering pain. The emergency medicine doctor can assess the patient and make the first intervention. If some aberrant values or conditions are observed, the doctor can send the results to a gynecology and obstetrics department colleague and discuss treatment on a mobile platform. If required, doctors from other departments can also be called on to decide on proper treatment.

In addition, medical users in emergency departments can use mobile applications for many purposes including deciding on treatment, such as required drugs, dosages, and alternative drugs. Before treatment, medical professionals can check the presence of chronic diseases or types of allergy which may affect their decision on treatment, by accessing past records of the patient through the hospital database or "e-Nabiz" platform, which will be discussed in the next section.

6.5.2 Utilization by Nonmedical User

Recently, mHealth has become accessible to nonmedical users. A common application in Turkey is the "e-Nabiz" system. This application can be downloaded to mobile phones or PDAs with Android or iOS operating systems. It is developed by the Ministry of Health as a "personal health system." It allows individual users to manage their own health records. It can easily be accessed with an identity number, e-State password, mobile signature, electronic signature, or personal credit card, and numbers of users are increasing daily.

Emergency processes are facilitated via the usage of "e-Nabiz." For patients using this application, all past record can be straightforward and rapidly accessed by all medical users. In addition, for patients visiting an emergency department, their health history will be immediately available.

"e-Nabiz" system includes a range of patient history information, including blood group type, chronic diseases, all health institutions visited, and all screening reports such as roentgen, tomography, magnetic resonance imaging (MRI), ultrasonography (USG), drugs taken, drug or any other type of allergy, and even information such as whether the patient is registered as an organ donor. A patient has the right to block access to any information considered confidential.

Some advantages of this system can be discussed. Consider a doctor who needs to view a patient's tomography to decide on proper treatment. If a patient has a recent computed tomography scan recorded in the "e-Nabiz" system, there is no need to repeat the procedure. This will be both time- and cost-efficient for providing treatment and will avoid exposure to additional radiation from tomography. Besides, if the patient allows, other doctors can also access such type of test results, enabling the most appropriate treatment. Another significant benefit of "e-Nabiz" platform is the provision of information on organ donation. Since many of the organs quickly decompose and receiving consent from family members is a time-consuming process, previously, transplantation was often not possible. Using the approval from the patient's personal health system, currently, the transplantation process is much faster.

Patients can also ask doctors questions about their treatment using mobile applications and request any type of test result or film from any hospital. Patients can also make appointments based on "The Pharmaceutical Track & Trace" System for any hospital departments except emergency medicine departments.

6.6 Barriers and Recommendation

Different mHealth tools and functions are in use in the emergency field and other areas of health in Turkey, as discussed in Sects. 6.4 and 6.5. However, various barriers hinder the utilization of mHealth. Cost is the main obstacle. Since implementing such technology-based systems is very costly, mHealth systems can become widespread if and only if governments and health insurance companies reserve the necessary funds for this investment.

Privacy and security are another challenge for mHealth systems as in line with WHO (2011) report. Unless people feel safe, the utilization rates cannot increase. In dealing with this problem, system providers need to take precautions. Regulatory issues also stand as a barrier. Therefore, governments need to focus on developing legal standards.

Logistics is one other challenge, as some rural regions still do not have an Internet access due to logistics problems. Interestingly, as discussed by Sariyer et al. (2017), when compared to urban regions, in rural areas, the demand for prehospital emergency services is much higher according to a number of calls per 1000 citizens. This can be viewed as highlighting the necessity for mHealth in rural regions, and governmental action is required to achieve this need.

In Turkey, technology usage and technology literacy are one of the biggest challenges in developing mHealth-based services. According to the Organization for Economic Co-operation and Development (2017) report, the percentage of households with Internet access is 69.5%, far below most other European countries. On technology usage numbers, Turkish Statistical Institute (TUIK 2016) reported that 44.8% of all members used a computer and 58.3% of them used the Internet in the last 3 months of 2016. Some statistics on computer usage in the last 3 months of 2016 according to age groups are summarized as follows: the percentage of the members who are aged 16–24 is 68.4%, it is 59.3% for the age group 25–34, 48.6% for the age group 35–44, and respective percentages of 31.2% 16.1%, and 6.5% follow for the ages of 45–54, 55–64, and 65–74. The similar percentages on the Internet usage statistics are, respectively, 84.3%, 78.8%, 65.4%, 41.3%, 21.0%, and 8.8%. Thus, it could be concluded that when the age increases, computer and Internet usage percentages decrease.

On the other hand, when the national statistics are compared according to gender, it could be seen that while 53.4% of all male members have used computers in the last 3 months of 2016, only the 36.3% of female used it. The respective percentages are 67.6% and 49.2% for male and female according to the Internet usage (TUIK 2016). This additionally shows that technology usage is lower in females in comparison with males. All these statistics show that implementing mHealth services is more difficult for elderly and females. Thus, the government and service providers need to take action to improve technology awareness and behavior, especially for these two groups. In Turkey, promotion campaigns, especially aimed at the elderly, as well as providing technological assistance are essential requirements.

When technology users are asked for their usage purposes, from TUIK (2016) report, it is understood that the most common goal is “participating in social networks” with the highest percentage of 84.3%. The government can use this information to prepare a route map for implementing mHealth to increase awareness. Social networks can be used to publicize all mHealth-related information and developments, and e-mails can be used for notifications and information sharing.

“Reading online news/newspapers/news magazines” is another common purpose of technology use (TUIK 2016). Thus, online newspapers can be recommended to share mHealth-related information. For example, a news magazine entitled “Medi-Magazin” in Turkey frequently downloaded and read by medical users can be used to increase awareness of mHealth implementation from medical users’ viewpoint.

Despite many challenges, mHealth, or using mobile tools and applications for health, can help people in managing their wellness, encouraging healthy lives, and reaching useful information when and where they are needed. In summary, mHealth has a capability to reshape healthcare policies and processes, the structure of healthcare, and the overall roles of medical and nonmedical users. Thus, implementation and utilization of mHealth services are crucial. The government and service providers urgently need to focus on compatible models for these services. Efficient and quick models and solutions can be generated if public and private organizations work collaboratively. In order to achieve this goal, main roles of these organizations can be listed as:

- Target users of mHealth are required to participate in preparing strategic plans.
- A guideline should be developed with the support of the government.

- Different pilot projects should be developed and evaluated with the input from various project teams, and the most effective ones should be executed to measure performance.
- mHealth business models should be developed.
- Increasing public awareness is very important.
- Private health insurance companies should be involved in this process.
- Utilization of health-related smartphone applications should be encouraged.
- Wellness-related apps and technologies should also be encouraged.
- The Ministry of Health should set standards for data recording, deleting, and storage of a "National Electronic Health Record" and "personal health record" databases.
- Legal standards are required to be developed for protecting security and privacy.
- Promotion campaigns are highly recommended to increase awareness.
- It is important to provide technological support and assistance especially for elderly, people in rural regions, and females.
- Technology and health literacy should be improved.
- Mobile applications and tools should be part of medical education, and they need to be used at all levels of education from the elementary school.
- Gamification is also recommended as an important way to increase awareness and utilization among young people.

Besides all these, the government needs to directly participate in significant projects and be closely involved in their implementation. For instance, a European project, aiming to restructure the next generation emergency services, "NEXES," could also be implemented in Turkey to improve emergency healthcare services. The main objective of NEXES Research and Innovation Action is to test and validate the integration of IP-based communication technologies and interoperability within the emergency services in order to increase their effectiveness and performance.

6.7 Conclusions

Although it is estimated that population growth rate will encounter a sharp decrease in the twenty-first century compared to the previous century, one of the greatest challenges facing the government and service providers is the increased length of life and hence increased expectations from health services. Due to increase in social welfare and the development of information and communication technologies, it is expected that health systems will be restructured in this century. Indeed, many of the fundamental processes of mHealth services emerged in the late 1990s, especially in developed countries. However, for many of the countries, including Turkey, these developments are still in process. Hence, many different steps still need to be taken to constitute sustainable and usable health services based on mobility.

In order to benefit from mHealth and generate sustainable systems, collaborative effort is needed from all those involved: the government, service providers, medical and nonmedical users, private organizations such as mobile operators or institutional companies, and other participants of this ecosystem. Without governmental support, regulatory support, and approval and utilization by the health sector as well as all users, the enormous potential benefits will not be fully realized.

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Chapter 7
User Adoption and Evaluation of Mobile Health Applications: The Case for Physical Activity Monitoring

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7.1 Introduction

Mobile applications are an effective approach to motivate individuals for healthy behavior, and recent years have seen an increase in the use of mobile and ubiquitous technology for changing human behavior or attitudes in the health domain. Behavior change support systems (BCSS) utilize persuasive technologies to assist users in pursuing their goals (Oinas-Kukkonen 2012), and they are widely used in health as well as welfare, commerce, education, energy saving, and other areas (Oinas-Kukkonen and Harjumaa 2008). With mobile and ubiquitous technology, behavior change techniques can be used to influence individuals based on their context, personal needs, and progress, and they have been shown to be effective particularly in mobile applications (Unal et al. 2014).

Physical activity applications have an important place among mobile health applications in terms of their wide popularity, commonality, and the need to use behavior change techniques to initiate and promote physical activity. Researchers have sought effective ways of encouraging physical activity and have shown that interventions designed to increase physical activity may improve success rate from 50% without intervention to about 70–88% with certain interventions (Dishman and Buckworth 1996). In this study, we aimed to investigate whether significant relationships exist between user adoption and evaluation of physical activity applications and features pertaining to behavior change interventions. To this end, we conducted hands-on research by obtaining mobile physical activity applications from the Turkish and US versions of Google Play Store. From the English and

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E. Sezgin et al. (eds.), *Current and Emerging mHealth Technologies*,
https://doi.org/10.1007/978-3-319-73135-3_7

Turkish versions of Google Play Store, we selected 78 top health and fitness applications in the following subcategories: fitness, workout, pedometer, and running. Each application was downloaded to a mobile phone to extract and classify all relevant features. To discover the significance and contribution of the features from the users' adoption and evaluation perspective, the relationship between features and an application's current rank in the store in terms of the number of downloads and rating was analyzed.

Our analysis of the relationship among features about the behavior change, user ratings, and download numbers revealed a significant relationship concerning download counts and nonsignificant relationship about the ratings. Furthermore, the subcategories of physical activity applications such as fitness, running, pedometer, and workout produced different results concerning their relation to behavior change support features.

7.2 Related Work

7.2.1 Behavior Change Features in Mobile Context

In recent years, the behavior change techniques used in mobile applications for physical activity have been analyzed by several authors using content analysis. Applications were rated based on the taxonomy of Abraham and Michie (2008) concerning the behavior change techniques used in interventions. The original study was designed for general interventions; therefore, the studies based on mobile applications had to interpret features of the applications and undertake some tailoring to fit the application context (Middelweerd et al. 2014). In the study by Middelweerd et al. (2014), the most frequently used behavior change techniques in mobile applications were found to be goal setting, self-monitoring, and feedback on performance as consistent with other types of intervention tool. The presence or absence of behavior change techniques was identified for physical activity and/or dietary behavior applications in research undertaken by Direito et al. (2014). The authors found that the most commonly used behavior change techniques provided instruction (83% of the apps), set graded tasks (70%), and prompt self-monitoring (60%). The limitation of these two studies lies in how they quantified the existence of behavior change techniques in the applications. The presence of a single feature in self-monitoring such as self-reports, diary, or route tracking in the application was deemed to be sufficient to label the application as exhibiting the related BCSS approach.

In the literature, there are a limited number of studies that investigated the effects of the features utilized in mobile physical activity systems. Munson and Consolvo (2012) found that the use of goals and reminders is more promising regarding positively affecting the user's activity in comparison to rewards and sharing. The use of reminders was the most appreciated feature indicated by all the participants, none of whom disabled this feature; however, expected rewards did not appear to motivate the users (Munson and Consolvo 2012). In their qualitative study, the users reported benefits from the use of both secondary and primary goals but considered that there were limited benefits in sharing their progress. In another qualitative study by Harjumaa et al. (2009), the most motivating of ten features were self-monitoring, reduction, and reminders. Praise and rewards were found to be effective only in some specific cases. In the qualitative study conducted by Dennison et al. (2013), recording and tracking behavior and goal and getting advice and information were valued by users, whereas context-sensing capabilities and social media interactions were found to be unnecessary and disturbing.

In the current study, we made use of some of the features mentioned in the literature (Middelweerd et al. 2014; Direito et al. 2014; Munson and Consolvo 2012). The main features, namely, self-monitoring, goal setting, rewards, and sharing, which were previously explored by Munson and Consolvo (2012), were further investigated through hands-on research using mobile physical activity applications obtained from the application store and examining related features.

7.2.2 Users' Adoption and Evaluation of Mobile Apps in the Market

The number of downloads and user ratings provide an insight into users' point of view and their adoption and evaluation of mobile applications in the mobile application market. The number of downloads gives commercially valuable information about an application; however, application stores only provide this information to application developers and avoid making the data public. Google Play Store is the only application market that gives information about the download statistics of all applications; however, instead of providing the exact value, they give download counts in buckets. One of the main reasons for using Google Play Store to select applications is the availability of the download data. Another characteristic of Google Play Store is that the majority of the applications are free. This allows us to obtain a set of uniform applications that compete on the same basis.

All application stores make user rating data available to the public, which provides valuable information concerning the consumer's perception of applications. Users can rate applications they have downloaded from 1 to 5 stars, with 5 being the highest possible rating. The average of these ratings is displayed in application markets for each application. However, there are serious drawbacks in using these ratings. Most importantly, the average rating is the average of multiple releases over time, which does not provide valid information for the user, who is interested in the latest release (Fu et al. 2013). Then, there are inconsistencies between user comments and ratings, which mostly result from careless mistakes or developers or their competitors' attempt to manipulate ratings (Shi and Ali 2012). Finally, ratings are usually polarized, with the vast majority of ratings being either 1 or 5. This is the case for Google Play Store, in which most applications are free, and users tend to give an application 1 star when it does not work and 5 when it fulfills their expectations (Shi and Ali 2012).

In the literature, a significant positive correlation has been reported between the number of downloads and user ratings for Android applications (Sunyaev et al. 2013; Dehling et al. 2015). Similar results were found in the Blackberry market, in which authors observed a strong correlation between ratings and downloads, and highly rated applications had the most frequent downloads (Finkelstein et al. 2014). A recent study in 2014 on Google Play Store concluded that although there was an expectation that applications with higher ratings would have higher download rates, this was not the case: All the paid applications had an average overall rating of 4 with free applications having an average overall rating that was greater than 4. On the other hand, combining both free and paid application, the average rating was between 4 and 4.5 in any bucket of the download range (Viennot et al. 2014).

7.3 Methodology

7.3.1 Data Collection Process

The application data was collected from the US and Turkish versions of Google Play Store. Free applications were targeted in the study because more users prefer to download free applications rather than paid ones (Mohan et al. 2013). The health and fitness category was selected in both versions of the store. In the Turkish version of the store, there was a list named Top Free Apps in the health and fitness category. The names, number of downloads, and rating values of the first 200 applications from the Top Free Apps list were recorded as of December 7, 2014. Google Play represents the number of downloads information as a range (e.g., 10–20 million). The minimum number of downloads within this range was recorded (e.g., 10 million). As a result, a total of 25 free applications were obtained from the US version of the store.

After obtaining the initial application lists from both stores, applications were included in the study based on the following criteria: (i) the language of the application should be English and (ii) the application should support a behavior change, i.e., it should direct or guide users to undertake physical activity. Applications that only provide information and guidelines about health or fitness but do not have behavior change features that encourage the user to undertake physical activity were excluded from further analysis. Five of the applications obtained from the US version of the store could not be downloaded due to differences in regional releases; therefore, they also had to be excluded. Additionally, nine applications from this store were already included in the applications from the Turkish store.

From the US and Turkish versions of Google Play Store, we selected 78 top health and fitness applications in the following subcategories: fitness, workout, pedometer, and running. The main reason for creating subcategories was to distinguish specific features of different types of applications. Of the 78 selected applications, 11 (14.1%) were from the US store, and 67 (85.9%) were from the Turkish store. First, all the applications were screened by one reviewer. Then, the applications were shared equally among three other reviewers each assessing the applications in terms of the presence of features related to behavior change. Thus, each application was reviewed by two different reviewers. All reviewers explored each application by downloading and using it with all the available functions. All the applications were installed on a smartphone with the Android operating system version 4.3. Each reviewer stated his/her opinion about whether the applications contained features related to behavior change techniques based on the taxonomy prepared and explanations of the features. For this purpose, Abraham and Michie's (2008) taxonomy of behavior change techniques used in interventions was adapted to the conditions of today's mobile technology, resulting in 34 items as presented in Table 7.1. In case of a conflict between two reviewers, a third reviewer screened the application that caused the conflict, and the features were extracted based on the opinion of the majority (2 of 3).

7.3.2 Data Analysis

In the analyses, dependent variables were selected as the number of downloads and rating of the selected applications. Independent variables were the features extracted related to behavior change. Table 7.2 shows the descriptive statistics of the dependent variables.

The Mann-Whitney U test is used to test for differences between two independent groups. In this study, this test examines whether there is a significant difference in the number of download or rating values in terms of presence of the features. In order to identify the important features on the dependent variables, we performed feature selection using the minimum-redundancy maximum-relevance (mRMR) method (Peng et al. 2005). It was shown that concerning feature selection and classification accuracy, mRMR achieved the lowest error rate compared with other algorithms such as Naïve Bayes, support vector machines, and linear discriminant analysis (Peng et al. 2005). The main aim of the mRMR algorithm is to find the features that best describe the target variable (i.e., the number of downloads and rating in the current study). The presence of these features in each application constituted our feature vector (FV1 = [a1, a2, a3,…, a13]). In other words, FV1 is a binary vector, which indicates whether the important features are present in the applications.

According to Cohen (1992), in order to conduct a statistical test measuring the difference between independent means, a sufficient number of data points are required. Cohen suggested 26 as the minimum number of data points to be included in a group in order to observe large differences between two groups. However, several features in our dataset had a lower number of data points than the given threshold. In order to not lose much data, we included the features having at least 20 data points.

Table 7.1 Availability of behavior change features in the selected applications

Feature	Number of apps having the feature	Number of apps not having the feature
Prompt practice	65	13
Provide exercise programs for each sport type	59	19
Self-reports	52	26
Prompt for hydration	50	28
Provide instruction on exercises	45	33
Share on Facebook	39	39
Reminders	34	44
Voice coach	30	48
Share on twitter	30	48
Share activity via other apps	30	48
Provide a social platform	25	53
Visualize activity statistics	22	56
Share on Google+	22	56
Select sport type	21	57
Share with community friends	21	57
Create own workout	11	67
Visualize routes on maps	11	67
Challenge previous performance levels	11	67
Share route and location	9	69
Message exchanges on social platform	9	69
Challenge with community friends	9	69
Challenge for a distance	8	70
Record favorite routes	7	71
News feed reporting others' activities	6	72
Link to music player	5	73
Prompt specific goal setting	4	74
Record heart beat	4	74
Link to smart watch	4	74
Get cheers from friends	4	74
Challenge to the finish line	4	74
Music list	4	74
Challenge with invited friends	3	75
Challenge for cal. reduction	3	75
Motivation song	2	76

Table 7.2 Descriptive statistics for the number of downloads and rating

	N	Minimum	Maximum	Mean	Std. deviation	Median
Downloads	78	1000	10,000,000	1,681,102.56	2,920,498.47	500,000
Rating	78	3.10	4.60	4.01	0.38	4.10

7.4 Results and Discussion

7.4.1 Findings on All Application Types

In each analysis for the feature we are studying, we have divided the applications into two groups: one group of applications with that feature and other group of applications without the feature. For example, we have investigated the differences between the number of downloads/ratings of applications having voice coach feature and without this feature. The difference between the presence of the features (FV1) on the number of downloads and the rating values was investigated using the Mann-Whitney U test since the number of downloads and the rating data were not normally distributed ($D(78) = 0.43$, $p < 0.05$; $D(46) = 0.17$, $p < 0.05$). Based on the results, the following features were found to be highly relevant with the number of downloads, given in order of the results of the mRMR test: voice coach ($U = 488.5$, $Z = -2.44$, $p = 0.02$), visualize activity statistics ($U = 304.5$, $Z = -3.55$, $p < 0.01$), self-reports ($U = 430.5$, $Z = -2.67$, $p = 0.01$), reminders ($U = 301$, $Z = -4.62$, $p < 0.01$), share activity summary via other apps on device ($U = 504$, $Z = -2.27$, $p = 0.02$), provide a social platform ($U = 238.5$, $Z = -4.65$, $p < 0.01$), and share with community friends ($U = 282.5$, $Z = -3.655$, $p < 0.01$). However, none of the selected features were found to be significant with rating ($p > 0.05$). This may imply that if an application provides these features, its number of downloads is expected to be significantly higher than that of the applications without these features. Furthermore, the order of features with a significant effect has important implications for system designers.

7.4.2 Findings on Subcategories: Workout, Pedometer, Fitness, and Running Applications

Forty-six of 78 mobile health applications (58.97%) were included in the category of workout. In order to determine the features that had an effect on the number of downloads and the rating values of workout applications, the mRMR algorithm was used. The order of features plotted in Fig. 7.1 shows that the first feature, message exchanges, is highly related with the number of downloads. The same analysis was performed for the rating values of workout applications. The relevant features are plotted in Fig. 7.2.

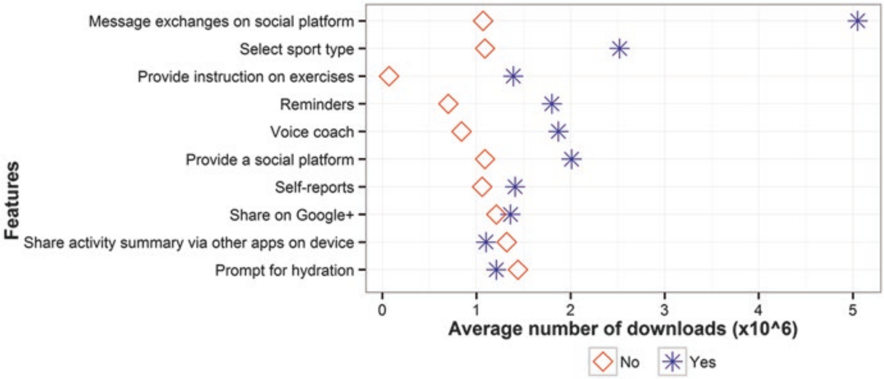

Fig. 7.1 Differences between the average numbers of downloads of workout applications with and without the given features

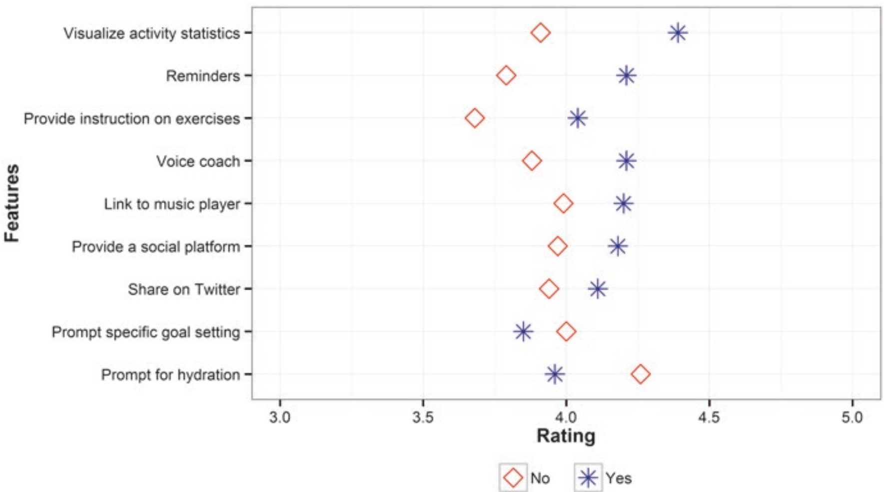

Fig. 7.2 Differences between the average ratings of workout applications with and without the given features

Fourteen of 78 applications (17.95%) were included in the category of the pedometer. Since the number of pedometer applications was less than 26, statistical tests could not be performed for these applications. Therefore, the highly relevant features with the number of downloads and the rating of pedometer applications were identified using the mRMR algorithm since it does not require a minimum number of data points contrary to other statistical tests reported by Ding and Peng (2005).

Figure 7.3 shows the differences between the average number of downloads of applications with and without the features given in the y-*axis*. The mRMR algorithm

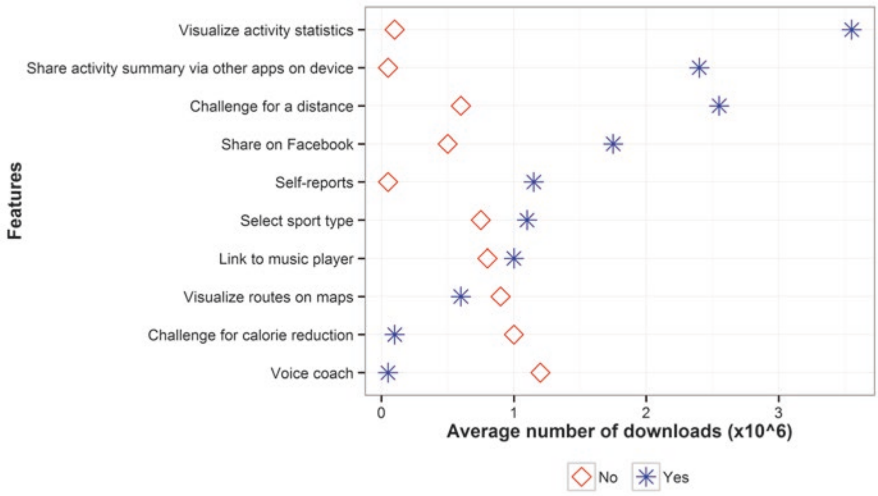

Fig. 7.3 Differences between the average numbers of downloads of pedometer applications with and without the given features

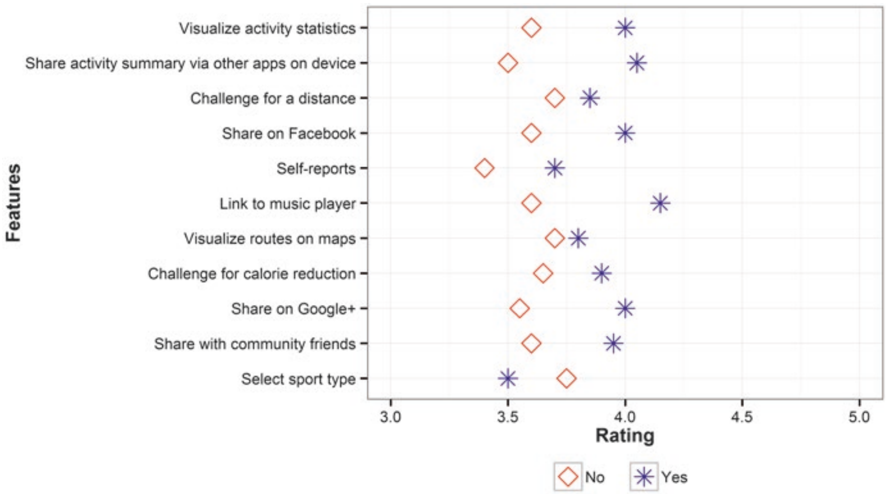

Fig. 7.4 Differences between the average ratings of pedometer applications with and without the given features

orders the features according to their effect on the number of downloads. The most significant feature was found to visualize activity statistics. Figure 7.4 presents a similar chart on the rating values. Figure 7.4 shows that the most effective feature on the rating values of pedometer applications is visualized activity statistics similar to the number of downloads.

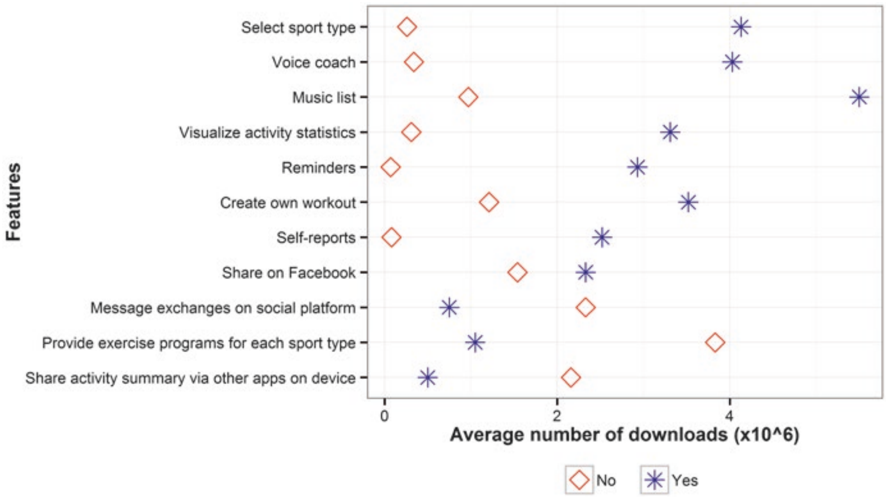

Fig. 7.5 Differences between the average numbers of download of fitness applications with and without the given features

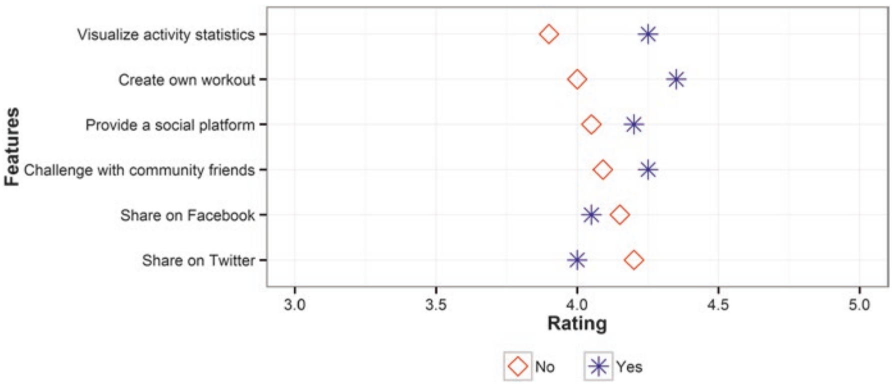

Fig. 7.6 Differences between the average ratings of fitness applications with and without the given features

Nine of 78 applications (11.54%) were included in the category of fitness. Similar to other types of applications, the mRMR algorithm was employed to identify the important features for fitness applications since the number of fitness applications was relatively lower (being only 9). The difference between the applications with and without the selected features in terms of the average number of downloads and average rating values are given in Figs. 7.5 and 7.6, respectively. The order of the features in the figures is given by the mRMR algorithm. Figure 7.5 shows that with the feature of message exchanges of social platform, the average number of downloads for applications without the given features becomes higher than those with these features.

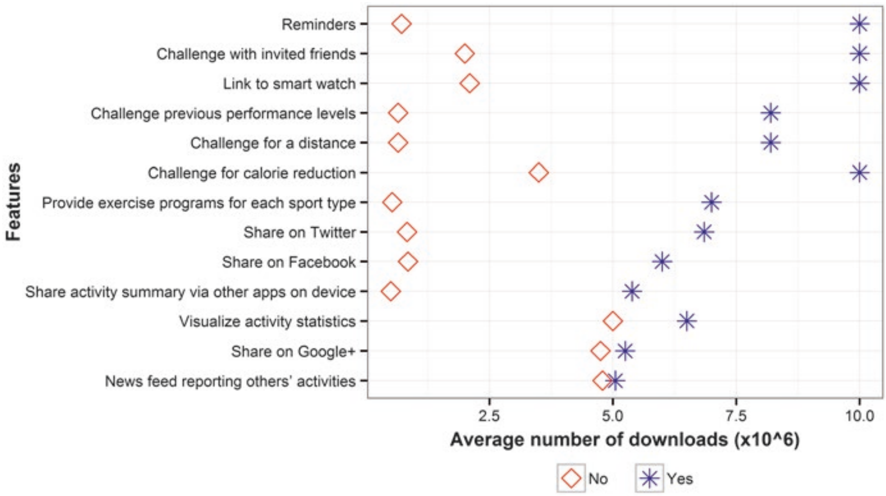

Fig. 7.7 Differences between the average numbers of download of running applications with and without the given features

The first seven features in Fig. 7.5 are highly related with the number of downloads. The average number of downloads of applications offering the feature of select sports type and voice coach is higher than that of applications without this feature. A similar result was obtained from the feature of visualizing activity statistics for ratings (Fig. 7.6). The mRMR values of both Share on Facebook and Share on Twitter are negative, meaning that they do not have a positive relationship with the rating values.

Nine of 78 mobile health applications (11.54%) were included in the category of running. Figure 7.7 shows that the average number of downloads for applications offering the reminder feature was about 10 million, whereas it was only about 1 million for applications without this feature. Similarly, there was a great difference regarding the features of a challenge with invited friends and link to smart watch. The differences become smaller as the features become less effective on the number of downloads (as going to the bottom of the y-*axis* in Fig. 7.7). When the rating values of running applications were compared, no major difference was found. Since the difference between the minimum and maximum values was not that high, it can be concluded that the rating values of running applications in this study do not substantially different as shown in Fig. 7.8.

7.5 Principal Findings

The current study aimed to explore the relationship between the number of downloads, user ratings, and support features promoting behavior change in health and fitness applications available in Google Play Store. This is the first study utilizing

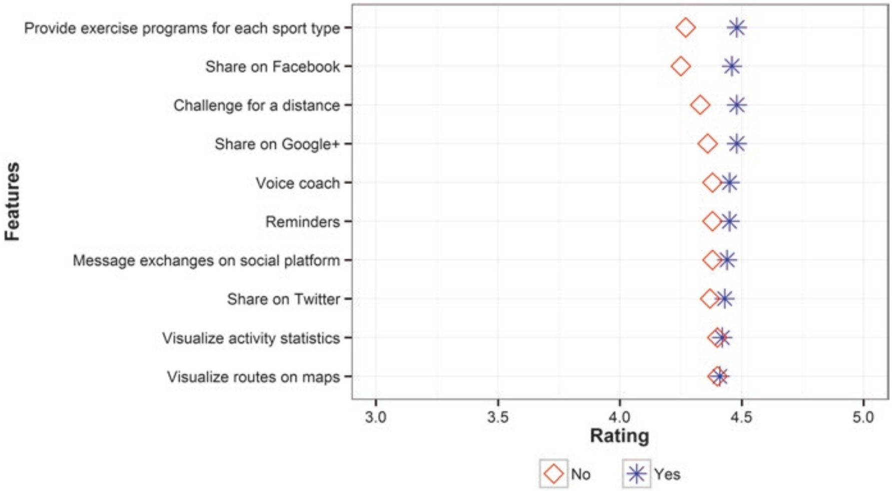

Fig. 7.8 Differences between the average rating of running applications with and without the given features

empirical hands-on research to determine the relation of the features in applications promoting physical activity with the number of downloads and user rating levels based on live data from users in the application store.

According to the results, the features of a voice coach, visualizing activity statistics, self-reports, reminders, sharing activity summary via other apps on the device, providing a social platform, and sharing with community friends have a significant relationship with the number of downloads. In the literature, reminders were also found to be the most contributing feature for users (Munson and Consolvo 2012). Sharing with friends on Facebook, Twitter, Google+, other applications, and communities was separately analyzed in this study. Similar to the results of the previous studies, sharing with Facebook friends did not contribute significantly to user ratings and number of downloads. In the previous studies, users reported limited benefits of sharing their progress on Facebook. Since information can be shared with all circles from family members to old friends, users are less willing to share personal information due to privacy concerns and social pressure obstacles (Oinas-Kukkonen 2012; Munson and Consolvo 2012; Ding and Peng 2005). Sharing with friends on Twitter, Google+, and other applications was explored for the first time in this domain, and they were also found not to be related with the number of downloads and user ratings. Providing a social platform and sharing with community friends were separately analyzed and found to be valuable for users. In agreement with the findings of the current study, in the literature, users reported benefits in disclosing their personal data to strangers and anonymous online communities (Ding and Peng 2005). These findings have significant implications for the differences between different modes of information sharing with others. The targeted audience in information sharing is important because people with whom information is shared can strongly influence individuals' motivation to pursue physical activity; thus, connecting individuals facing similar challenges would have a comforting and encouraging effect and can facilitate social support. No significant relation was found between any of the features and user ratings. This may be due to the strong inclination to give high ratings to free applications and Google Play Store applications as mentioned in the literature (Finkelstein et al. 2014; Viennot et al. 2014). Another reason may be the small sample size of each evaluated feature.

In studies that performed content analyses in the literature, rather than exploring the effectiveness of features, the frequency of using behavior change techniques was investigated. Although this is a fundamental difference in methodology, some of the most frequently used behavior change techniques overlap with the most relevant features in our study. In the study by Middelweerd et al. (2014), the most frequently used behavior change techniques were found to be goal setting, self-monitoring, and feedback on performance. Direito et al. (2014) reported provide instruction, set graded tasks, and prompt self-monitoring to be the most prominent techniques. In our study, the features that were found most relevant were reminders and voice coach, which are related with provide instruction and goal setting. Visualizing activity statistics, providing a social platform, and sharing activities can be considered relevant to self-monitoring and feedback on performance.

For pedometer applications, visualizing activity statistics, sharing activity via other applications, and challenging friends for a distance were found to be the most relevant three features in terms of the number of downloads, whereas for running applications, the most relevant three features were reminders, challenging invited friends, and link to smart watch. The features that were most relevant for running applications seemed to fit the domain since reminders, challenging invited friends, and link to smart watch were the features in running applications that received higher download counts from users. On the other hand, for pedometer application users, visualizing their statistics and sharing them on other applications, e.g., through providing a link to gadgets, received higher download counts. When the features and the ratings of pedometer applications were considered, the most relevant three features were the same as those obtained from the number of downloads. However, for running applications, providing exercise programs for each sports type, sharing on Facebook, and challenging friends for a distance were the three most relevant features for rating. One factor on the discrepancy between the relevant features in terms of the number of downloads and rating of running applications can be related to how the particular features are implemented, i.e., the user interface and usability. Our findings clearly show that there is a large discrepancy between the reasons for downloading an application and its final rating. Furthermore, these discrepancies vary depending on the type of physical activity. This can be attributed to users not being satisfied with the quality or implementation of the features that initially attracted them to download the applications. Application developers can use our findings to improve these features in order to enhance the efficacy and usability of their applications and thereby improve the ratings of their applications.

The findings of this study show that physical activity applications can be substantially improved using applied behavior change techniques. This would create an opportunity to develop more sophisticated and effective mobile applications that address user needs and priorities. The implications of this study will guide designers of mobile physical activity applications to enhance user adoption and evaluation and provide them with a better insight into which features work better through successful interventions intended for behavior change.

7.6 Strengths of the Study

Previous studies have either assessed mobile physical activity applications by using content analysis or conducting qualitative techniques to determine the effectiveness of features pertaining to behavior change techniques. To the best of our knowledge, this is the first empirical study to evaluate the presence of a relationship between application features and live data on the number of downloads and ratings from the Google Play Store.

In previous studies that conducted a content analysis of mobile physical applications, behavior change techniques were rated. One of the strengths of our study is that we explored, in more detail, the specific features pertaining to the same behavior change techniques. Thus, we had the opportunity to discriminate between sharing on Facebook and sharing with community friends, and we found completely different relations.

7.7 Limitations

The present study has a few limitations. First, the analysis was limited to the applications in the Google Play Store since it is the only application store that provides download counts. Second, even though both the Turkish and US versions of Google Play Store were used, the analysis was limited to English language applications. Therefore, there is a need for further research on applications listed on other English and non-English language versions of Google Play Store. Another limitation is the use of only free applications. Since the majority of applications are free in Google Play Store, there was only a uniform set of applications available to conduct a statistical analysis.

One other limitation of the current study is that a detailed statistical analysis could not be conducted on the subcategories of physical activity, which were workout, pedometer, running, and fitness, due to the limited number of applications analyzed for each category. Therefore, further research is needed. Lastly, there was no follow-up research after downloading and using applications for a period of time. Therefore, the effects of rewards, which are rather devoted after the use of features, could not be properly analyzed in our research.

Despite the limitations, this study is significant in terms of being the empirical quantitative research on user evaluations regarding mobile physical activity applications in terms of a number of downloads and ratings and behavior change feature. To better understand the effectiveness of features, further research can be conducted to determine how frequently and for how long these applications are used.

7.8 Conclusion

Our hands-on research approach helped us understand the effects of features on users' adoption and evaluation of mobile applications in the physical activity category. Based on our findings, when designing and developing mobile health applications, designers can focus on certain features relevant to the type of application to improve user adoption and evaluation. These specific features can be added to applications to enhance the effects of behavior change interventions for the mobile health domain. The theoretical ground can be incorporated into mobile applications with the help of clinicians and experts on health behavior change systems to develop applications that better address user needs.

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Chapter 8
Unintended Users, Uses, and Consequences of Mobile Weight Loss Apps: Using Eating Disorders as a Case Study

Elizabeth V. Eikey

8.1 Introduction

Ava had just started college, and she was excited to make new friends and have some independence. It was her first time away from home, so she was learning how to navigate this new chapter of her life. Ava never cooked much at home; her mom and dad often prepared her meals. Now that she was living in the college dorm, home cooked meals were few and far between. Without a stove or oven, she found herself eating at her school's dining commons often. Eating and drinking alcohol also became an integral part of her social life. On the weekends, she and her friends would go out drinking and get some late-night food on their way back to their dorm rooms. By the end of her first semester, Ava noticed she had gained five pounds.

She was technically within a healthy weight range according to her body mass index (BMI),[1] *but she did not feel very comfortable with her body anymore. It was getting easier and easier to compare herself to the other women around campus. "They're so pretty and skinny," she thought to herself. Ava never worried about her weight or what she ate. She did not know much about nutrition, but she never really felt she had to. She stayed active by playing sports in high school, and she was always thin. But now Ava felt like she had to lose weight, and she wanted to lose it quickly. A quick search for applications (apps) on Google Play for "weight loss" revealed thousands of results. She picked one with high ratings and a lot of downloads. After downloading the app, she set a weight loss goal of ten pounds at two pounds per week, and the app gave her a daily calorie budget. Ava thought that if she ate under the allotted calorie budget, she would lose even more than two pounds*

[1] For adults 20 years+, underweight is <18.5, healthy weight is 18.5–24.9, overweight is 25.0–29.9, and obese is 30+. For younger users, BMI is calculated using percentiles. Anything <5th percentile is considered underweight.

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E. Sezgin et al. (eds.), *Current and Emerging mHealth Technologies*,
https://doi.org/10.1007/978-3-319-73135-3_8

each week and thus reach her goal weight more quickly. Soon it became a competition to see how many calories she would have remaining. Each day she felt compelled to eat less than the day before. Thoughts of food started consuming her everyday life, and the need to precisely track every bite of food was interfering with her schoolwork and friendships.

This story, a reflection of actual experiences expressed by college-aged women in the United States, exemplifies the unintended users, uses, and consequences of mobile health apps for weight loss. This chapter seeks to draw attention to user groups that may not represent the intended or "ideal" user when mHealth applications are designed. Without thinking beyond the intended users and uses, our technologies may negatively affect users, especially when we think about users' health (both mental health and "physical" health). To ground these ideas, eating disorders are used as a case study. Thus, the focus of this chapter is on weight loss app users who exhibit eating disorder behaviors or disordered eating behaviors, their use of these apps, and the impact these apps have on them.

Eating disorders are on the rise (Engel et al. 2007). It is estimated that 30 million people in the United States have an eating disorder, and many more have unhealthy eating behaviors (Reba-Harrelson et al. 2009; Wade et al. 2011). While eating disorders are increasing among males (Strother et al. 2012), females are more likely to develop eating disorders (Fairburn and Harrison 2003). Eating disorder behaviors or disordered eating includes behaviors associated with eating disorders, such as purging, bingeing, rigid exercise regimens, anxiety about food and weight, and body image concerns.

Researchers have found that 31% of women without a history of anorexia nervosa or binge eating reported having purged to control weight, and 74.5% reported that their happiness was negatively affected by their body and weight concerns (Reba-Harrelson et al. 2009). Additionally, research has shown that 25% of college women have engaged in bingeing and purging as a weight loss method (Wade et al. 2011), and over 50% of adolescent girls have skipped meals, fasted, smoked cigarettes, vomited, or taken laxatives to manage their weight (Neumark-Sztainer 2005). It is estimated that 8–17% of college-aged students have an eating disorder, and 20% of college students believe they have had an eating disorder in their lifetime (Hoerr et al. 2002; Reinking et al. 2005; Eisenberg et al. 2011). For example, Eisenberg et al. (2011) found that 13.5% of undergraduate women had positive screens for eating disorders. The difference between disordered eating and eating disorders is the degree of severity. The problem is that many people are reluctant to seek treatment even if they feel they have an eating disorder (Livingston and Boyd 2010). Instead, they may turn to technology (Kummervold et al. 2002).

In the following sections, a discussion of the use of mHealth apps for weight loss is provided. Then we explore the unintended users of weight loss apps. An unintended user refers to a person who uses technology but is not representative of the person the designer or developer originally intended as the user. To highlight that users with eating disorders are already using these types of apps, this chapter points specifically to users' profile data from a popular weight loss app. Next, we focus on unintended uses of these apps. Unintended use refers to how people utilize apps in ways for which the apps were not specifically designed. In the case of eating disorders, this typically means users use the apps to maintain their eating disorders or support recovery efforts. We then investigate the unintended consequences, or unanticipated outcomes, of weight loss apps using qualitative data (from both forum posts and interviews), previous work, and popular media articles. Finally, implications in terms of design, healthcare, and education are discussed.

8.2 mHealth Apps for Weight Loss

Technology is playing an increasingly important role in people's lives, especially in terms of health. Weight loss apps are becoming more popular and can be useful tools to track diet, exercise, and weight (Fox and Duggan 2012; Smith 2015). Researchers have studied ways to design these apps in order to encourage healthy food choices and physical activity (Choe et al. 2014; Mueller et al. 2014; Walsh and Golbeck 2014; Cordeiro et al. 2015; Stawarz et al. 2015). The focus has primarily been on how to design these apps to encourage overall wellness, healthy diet, weight loss, and/or physical activity (Cordeiro et al. 2015; Rooksby et al. 2015) and how this technology contributes to users' ability or their perception of their ability to achieve health goals, such as weight loss and exercising (Choe et al. 2013). Some of this work has focused on how design and features of wellness, weight loss, diet, and fitness technology impact users (Toscos et al. 2006). In much of this research, the users are typically viewed as a single group with little attention to the various needs of different types of users, often the unintended users. While there is some individualization to weight loss apps, users are often viewed as having the same issues, centered on weight loss.

8.2.1 Use of Mobile Weight Loss Apps in Relation to Eating Disorders

There may be aspects of weight loss apps that are helpful for eating disorder recovery; however, there may also be aspects that impede user recovery or promote the maintenance of eating disorders. Prior studies have found that some technologies, especially those that facilitate social support, can be beneficial to users with eating disorder behaviors (Whitlock et al. 2006; Bowler et al. 2012). On the one hand, research has shown that people with behaviors indicative of eating disorders use technology to maintain the symptomology of their disorder (Keski-Rahkonen and Tozzi 2005; Ransom et al. 2010). On the other hand, technology can also be used to aid in eating disorder recovery (Whitlock et al. 2006; Bowler et al. 2012; Juarascio et al. 2015). However, there has been little research examining the role of weight loss apps in enabling eating disorders or in supporting eating disorder recovery and maintenance.

Weight loss apps enable and promote dieting, which is a risk for developing an eating disorder (Shisslak et al. 1995; Neumark-Sztainer et al. 2006). In fact, women who severely diet are 18 times more likely to develop an eating disorder, and those who moderately diet are 5 times more likely to develop an eating disorder than those who do not (Neumark-Sztainer et al. 2006). Aggravating this problem is the fact that these behaviors may be viewed as typical to achieve weight loss. Even when individuals recognize their eating and exercise behaviors are interfering with their lives, they may avoid seeking help due to the stigma associated with eating disorders (Livingston and Boyd 2010). Research has shown that users with eating disorders find it easier to discuss their issues online as opposed to face-to-face (Kummervold et al. 2002), which may explain why users are turning to weight loss apps.

While weight loss apps may intend to promote healthy diets and exercise, they may unintentionally encourage habits indicative of eating disorders because they focus heavily on calorie intake and deficits and weight. This can be problematic for users who have eating disorders because it may encourage and exacerbate symptoms, which can lead to additional physical and mental health problems. Furthermore, healthcare providers are encouraging their patients to track their diet and exercise behaviors using health apps in order to create tailored health plans. Consequently, we need to understand weight loss app users better, how they use apps, and the consequences of use, especially in terms of eating disorders.

Users with eating disorders or disordered eating can be viewed as unintended users of weight loss apps because weight loss apps are not designed to support people with eating disorders, and many are not even designed to help people gain weight. For instance, even apps that allow users to set weight gain goals encourage users to eat less than their allocated calories through visualizations. Yet users with eating disorders still seek out weight loss apps. Because weight loss apps were not designed with their unique needs in mind, users with eating disorders have to appropriate these apps to meet their needs, which means they may have to use the app in ways not intended by the designer or developer. Using technology not necessarily designed for them, users with eating disorders may experience unintended consequences not even considered during app development.

8.3 Unintended Users

We tend to design technology for "intended" users but often do not really explore how other people, or unintended users, may use our technology. Often we have an ideal user in mind, but people are complex; they usually cannot be whittled down to one health condition or need. So while weight loss apps are intended for people who need to lose weight, what happens when those users may need to lose weight but have other health conditions that may influence how the app is used and the app's impact on the user? What if the user has diabetes, depression, binge eating disorder, or had anorexia nervosa in the past? What if they know very little about nutrition? What if they have poor body image or are predisposed to developing an eating disorder? These users may not fit the target user, but they are using weight loss apps to lose weight nonetheless, and there is some, albeit new, research to support this idea (see Eikey and Reddy 2017).

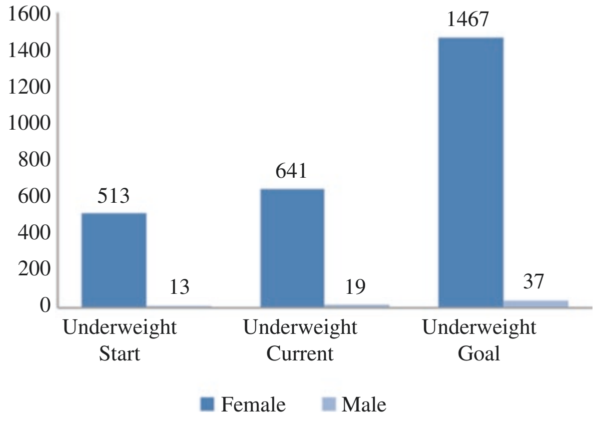

Fig. 8.1 Underweight start, current, and goal BMI by gender

In Singapore, for example, researchers conducted a survey and found participants with eating disorders use weight loss apps (Tan et al. 2016). In one study, we recruited and interviewed women who had an eating disorder and used weight loss apps, such as MyFitnessPal (Eikey and Reddy 2017). In another study, my colleagues and I conducted an analysis of profile data and forum posts within an online community associated with a popular weight loss app, DropPounds,[2] and found a number of users discuss having eating disorders (Eikey et al. 2017)[3]. With 5,000,000–10,000,000 downloads according to the Google Play Store as of September 2016, DropPounds includes many of the features and content found in the majority of weight loss apps. For example, it allows users to track their diet and activity and has an optional online community associated with it, which users can turn to for advice and support.

Looking closer at DropPounds, a number of its users recorded unhealthily low weights and set low weight goals. The company that owns and operates DropPounds provided user data in 2012. Although they had over a million users, only 19,710 users had information in the dataset. After removing users with a start BMI[4] under 10 and users with a BMI over 104, 19,418 users remained. Of those users, 2.71% (n = 526) had underweight start BMIs, 3.40% (n = 660) had underweight current BMIs, and 7.75% (n = 1504) had underweight BMI goals. The gender breakup is shown in Fig. 8.1. The overwhelming majority of users with underweight BMI were identified as female.

Interestingly all users with underweight start BMIs wanted to either stay the same weight (n = 32) or lose weight (n = 494), which means no user who started

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[2] App name was change to protect users' privacy.

[3] The referenced article was written and published after this book chapter. Therefore, some information reported has been updated.

[4] Due to lack of accurate age data for some users, all BMI calculations were performed using the standard BMI calculations (no percentiles). DropPounds requires users to be at least 18 years old. However, it is possible some users misreported their age in order to use the app.

with an underweight BMI wanted to gain weight to be in the healthy range. This data shows a subset of DropPounds' users is underweighted or aspire to be. Having a desire to be underweight and drive for thinness is associated with eating disorder behaviors and eating disorders (Boero and Pascoe 2012; Peñas-Lledó et al. 2015). Users who are trying to reach an unhealthily low body weight or users with a history of eating disorders are not the intended population of weight loss apps but still use them.

8.4 Unintended Uses

With an ideal user in mind, designers and developers are not going to focus on the needs of unintended users because those users may not even cross their minds. Thus, it is easy to see how unintended users would have to appropriate technologies to suit their needs and goals. For instance, users with eating disorders create online spaces for unintended purposes and utilize existing technologies like weight loss apps in unintended ways.

8.4.1 Pro-eating Disorder Communities and Social Media

A great deal of research has looked at how people create and use pro-eating disorder online communities, forums, blogs, and websites. Pro-eating disorder content often focuses on eating disorders as a lifestyle choice rather than a disorder requiring treatment. On pro-eating disorder sites and forums, users share information on how to lose weight and essentially maintain the symptomology of eating disorders (Sharpe et al. 2011). Online content that promotes disordered eating is often associated with "pro-ana" or "pro-mia" communities (short for pro-anorexia and pro-bulimia). These communities are created and maintained as spaces for users living with anorexia nervosa or bulimia nervosa to promote and encourage disordered behavior rather than alter it. While these communities can offer emotional support and a sense of community, the messages and content focus on sustaining disordered eating, not recovery (Csipke and Horne 2007; Sharpe et al. 2011). While websites and forums were not intended to support unhealthy eating and exercise behaviors, users have created eating disorder-specific websites and communities through these mediums.

More recently researchers have begun to consider how non-eating disorder-specific technology (technology not for eating disorder recovery or promoting eating disorder behaviors) is used (Chancellor et al. 2016; Pater et al. 2016; Eikey and Booth 2017). For example, Pater et al. (2016) analyzed hashtags on Tumblr, Instagram, and Twitter and found pro-eating disorder-related hashtags, images, and text despite these platforms' attempts to remove this type of content. Similarly, Chancellor et al. (2016) found that despite Instagram's strategies to reduce pro-eating disorder content, pro-eating disorder communities still exist and are thriving. In addition to promoting eating disorder behaviors, users with eating disorders also use Instagram as a space to showcase, track, and promote eating disorder recovery. These studies demonstrate that users with eating disorders are utilizing even general-purpose technologies, such as social media. These social media platforms were not originally intended to support eating disorders in any way and likely were not designed to do so.

8.4.2 Weight Loss Apps

Despite the recent push to understand the use of non-eating disorder-specific technologies, there is not much research on how weight loss apps are being used in relation to eating disorders. Yet there is evidence to show that users with eating disorders are appropriating weight loss apps. Specifically, there are three potential ways users with eating disorders are using weight loss apps in unintended ways: to maintain symptoms of eating disorders, to lose weight when weight loss is unnecessary, or to aid recovery from an eating disorder.

As stated before, prior research has found that people with eating disorders utilize technology to maintain the symptoms of their eating disorder. However, when it comes to weight loss apps, study data suggests that some users are not even aware of their eating disorders when they seek out a weight loss app (Eikey and Reddy 2017). Instead, they want to lose weight and find an app to help them. Like the vignette at the beginning of this chapter highlighted, users' behaviors may spiral out of control. Users may feel the need to compete with themselves and further restrict their calories or exercise in excess to compensate for eating. Many users also have an intense fear of gaining weight and feel as though they need the app to manage their weight and food intake. They are often very numbers-focused and get a great sense of achievement by using the app. Without the app, they feel like they are out of control. This seems especially true for those with a history of eating disorders, those who may have poor body image, or those who are generally predisposed to developing an eating disorder.

In a recent study, my colleague and I examined how weight loss apps are being used by college-aged women with eating disorders (Eikey and Reddy 2017). Through interviews, we found that women's use of weight loss apps is a dynamic process that changes as they go through their health journey. At some points, they use the app to support unhealthy behaviors with a weight loss goal in mind. When users want to be healthier and still want to use the app to manage their health, they use the app for recovery. In this case, the app is a tool to help them learn to add calories and eat more instead of restricting calories. In addition to an interview-based study, in our analysis of DropPounds' forum posts, we also found users reported using the app for recovery (Eikey et al. 2017). While some users may use weight loss apps as a tool for recovery, these apps were not intended to be used in this way and thus are not designed for eating disorder recovery. This means the consequences of using weight loss apps in relation to eating disorders have not been thoroughly considered.

8.5 Unintended Consequences

Unintended uses and consequences can go hand in hand. When technology is used in a way not necessarily intended by the designer, developer, or company who operates the technology, there are often unintended consequences. The term “unintended consequences” refers to unforeseen or unpredicted results to a specific action (Campbell et al. 2006). This terminology is common in discussing the technological impact, especially related to health information technology. These consequences can be positive, negative, or neutral.

8.5.1 *Pro-eating Disorder Communities and Social Media*

Going back to pro-eating disorder communities, some argue that pro-eating disorder communities may actually have unintended positive consequences on users. Some researchers have found that pro-eating disorder communities and sites offer support, a sense of community, and a coping mechanism for users with a stigmatizing condition (Mulveen and Hepworth 2006; Csipke and Horne 2007; Sharpe et al. 2011). Users who interact with other users and seek emotional support reported increased positive mental states after visiting those sites (Csipke and Horne 2007). In addition, these communities can actually have positive effects on behaviors by promoting healthy eating (Ransom et al. 2010). This highlights the importance of creating technology to be inclusive. User exposure to these communities can also reduce the impact from potentially harmful content (Csipke and Horne 2007).

However, many researchers have found that pro-eating disorder communities have unintended negative effects on users. Some researchers believe that these sites are a façade of “support” but actually are anti-help-seeking and anti-recovery (Rouleau and Von Ranson 2011). While users report an increase in perceived support, these communities actually exacerbate their symptoms (Csipke and Horne 2007; Rouleau and Von Ranson 2011) and perpetuate unhealthy habits (Ransom et al. 2010). For instance, Csipke and Horne (Csipke and Horne 2007) found pro-eating disorder communities worsened eating disorder symptoms of users who are “silent browsers” (i.e., users who do not actively interact with the community). Pro-eating disorder communities have been associated with higher levels of body dissatisfaction (Grimes and Harper 2008; Jett et al. 2010), higher levels of eating disturbance (Harper et al. 2008; Jett et al. 2010; Peebles et al. 2012), greater negative affect (Bardone-Cone and Cass 2006, 2007), lower social self-esteem (Bardone-Cone and Cass 2006, 2007), lower appearance self-efficacy (Bardone-Cone and Cass 2006, 2007), decreased perceived attractiveness (Bardone-Cone and Cass 2006, 2007; Custers and Van den Bulck 2009), perception of being overweight (Bardone-Cone and Cass 2006, 2007), higher drive for thinness (Custers and Van den Bulck 2009), perfectionism (Custers and Van den Bulck 2009), increase in harmful activities (such as diet pill abuse and self-injury) (Peebles et al. 2012), lower quality of life (Peebles et al. 2012), and increased hospitalization rates (Peebles et al. 2012).

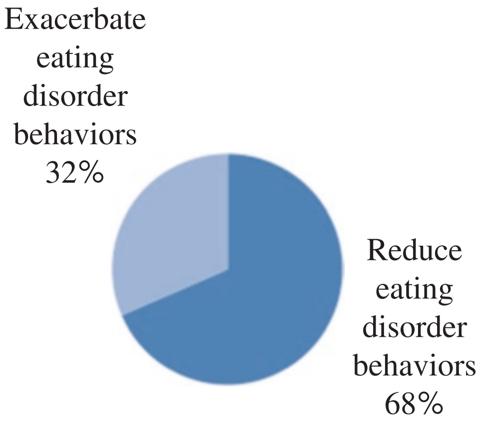
In addition to pro-eating disorder communities, researchers have also considered the unintended consequences of general-purpose technologies, such as social media. Research has focused on how social media may unintentionally and negatively impact users' body image and eating disorder behaviors. A great deal of this research has examined the ways in which social media can influence eating disorder risk factors (Andsager 2014; Mabe et al. 2014; Meier and Gray 2014; Fardouly et al. 2015; Stronge et al. 2015). For example, Kim and Chock (2015) conducted an online survey to examine Facebook's impact on the drive for thinness. They found engaging in social behaviors, such as checking friends' profiles, leaving messages, and commenting on profiles, is correlated with the drive for thinness in both females and males (Kim and Chock 2015). Fardouly et al. (2015) studied the effects of Facebook on female university students' body image and found the frequency of Facebook use was related to body image concerns. Stronge et al. (2015) found that both female and male Facebook users tend to have poor body satisfaction. Similarly, Mabe et al. (2014) found that frequency of Facebook use was related to disordered eating. Other researchers have studied hashtags and photos on sites such as Instagram and Twitter. For instance, Tiggeman and Zaccardo (2015) discuss how "fitspiration" can have unintended negative effects on college-aged girls. In her analysis of fitness blogs and media culture, Stover (2014) argues that "fitspiration" is dangerous in that the images and text are more "culturally acceptable" than those that showcase emaciated subjects. However, "fitspiration" still promotes a narrative that encourages users to compare and monitor their bodies.

8.5.2 Weight Loss Apps

Weight loss apps may unintentionally exacerbate and trigger eating disorder symptoms. From a survey of 55 participants in Singapore, participants reported both unintended positive and negative consequences of apps (Tan et al. 2016). While weight loss, diet, and exercise apps were not the main focus, they found that of the 41.8% of participants who felt apps, in general, helped them continue their eating disorder, 26.1% reported weight loss, diet, and exercise apps specifically helped continue their eating disorder. Of the 32.7% of participants who felt apps in general helped with recovery, 15.8% reported weight loss apps aiding eating disorder recovery. However, this research did not go into more detail about how these apps helped continue eating disorders or recover from them.

From the DropPounds data, of the 1036 eating disorder-related threads, we randomly sampled 58% of these threads (600 coded threads, 3139 coded posts) before we reached data saturation (Marshall 1996). Three percent (n = 95) of all coded posts discussed the effects of weight loss apps. Of those posts, two posts were duplicates, and one post did not specifically pertain to the DropPounds but another app. Within the remaining posts (n = 92), users expressed how the app impacts them in both positive (n = 63 posts) and negative ways (n = 29 posts) (see Fig. 8.2).

Fig. 8.2 Percentage of posts related to the consequences of DropPounds



When specifically focusing on users with underweight BMI goals, users reported that DropPounds aggravates symptoms because it focuses too heavily on weight and calories and allows unhealthy eating plans. This leads to more purging and restricting as well as obsessive thoughts and behaviors. Similarly, in interviews with women with eating disorders, participants reported weight loss apps reinforced obsessive logging, the need to be precise, and made them acutely aware of the numbers associated with food (Eikey and Reddy 2017). From the DropPounds' data, users felt the app helped with their recovery by providing a visual representation of their behaviors and a set healthy plan, which reduced bingeing and restricting and led to improved food choices. During interviews, some users also discussed the visual representation helped them know where they could add more calories to their diet (Eikey and Reddy 2017). In spite of wanting to recover, however, participants felt that they often reverted to old, unhealthy habits when using weight loss apps (Eikey and Reddy 2017).

Some popular media articles have also emphasized the negative impacts of weight loss apps (Miller 2015). For instance, Miller (2015) reported that diet- and activity-tracking technologies feed the eating disorder mentality by focusing on control and perfectionism. The emphasis on logging and quantifying weight, diet, and exercise fuels obsessions and compulsions to reach unrealistic goals, especially for those who already have disordered eating behaviors (Miller 2015). Similarly, in an article in *The Guardian,* a psychiatrist who specializes in eating disorder treatment estimated that "75% of her young-adult patients use their mobile phones in a way that enables their eating disorders" (Mahdawi 2014). In the article, Mahdawi (2014) said that "apps that facilitate calorie-counting and food-logging are an anorexic's best friend and worst enemy" and that "with society increasingly embracing a sort of 'techorexia' that rewrites compulsive behavior as healthy, it is becoming easier for people with serious eating disorders to pretend there's nothing wrong." These studies and popular media articles show both negative and positive unintended consequences of using weight loss apps.

8.6 Implications

This research has a number of implications. Developers and designers need to consider unintended users, uses, and consequences, which may lead to design changes, and researchers should examine this area further. This research also has implications for healthcare providers to consider how technology plays a role in the development of eating disorders. Finally, this work sheds light on potential directions for health education.

More developers, designers, and researchers need to consider the unintended users, unintended uses, and unintended consequences when developing, designing, and employing any technology but especially health technology, such as mobile weight loss apps. We cannot always predict these, but that is where research can make a difference. We need to study how technology is used to know how it may be unintentionally used. Qualitative methods, such as in-depth interviews, are valuable tools to understand users' lived experiences and uncover important research questions that we may have otherwise not known to pursue. When we know how technology may be used, we become privy to its consequences. We see things in a way we would not have otherwise seen them, leading to new insights and even innovations. In order to make more of an impact, more collaboration is needed between academia and industry.

In healthcare, providers need to be aware of current technologies like weight loss apps and how their patients may be using these apps in order to understand the best treatment approach. Some researchers have urged clinicians, caregivers, researchers, and institutions to be aware of the existence, possibilities, dysfunctions, and impact of technology in relation to eating disorders (Castro and Osório 2013; Teufel et al. 2013). In the diagnosis and treatment of eating disorders, clinicians need to assess "the online activity of their patients to identify contributing factors, such as engagement in pro-anorexia communities, and provide guidelines about a safe use of the internet since a simplistic approach based on banning the Internet will limit access to trustworthy health information and to support from pro-recovery communities" (p. 8) (Yom-Tov et al. 2012). While research has shown that people with eating disorders use and are affected by weight loss apps, few researchers have examined how providers view and understand the role of weight loss apps in the diagnosis and treatment of eating disorders (Eikey 2016).

Issues may begin with good intentions (such as, I want to lose weight, I want to exercise more, I want to eat better) but result in disordered behaviors and even eating disorders. Lack of nutrition knowledge is rampant, especially in the Physician's Committee for Responsible Medicine (2012). If we wish to prevent eating disorders, then nutrition must be more carefully incorporated into curricula early, and we need to find ways to reinforce proper nutrition in the school and home environment.

8.7 Conclusion

In designing and developing technology, we must be aware of the unintended users, uses, and consequences of our technology, especially mHealth. Users are complex humans and do not often fit the ideal user. This disconnection between the ideal user and the actual user results in the technology being used in unintended ways, which often leads to unintended consequences. There may be unintended negative consequences and unintended positive consequences. To design the most effective mHealth apps, we need to consider both. Especially when it comes to health, there are real-life issues that can arise when negative impacts are not addressed, and there can be real benefits to understanding unintended positive consequences.

Acknowledgments This material is based upon work supported by the National Science Foundation under Grant No. DGE1255832. Any opinions, findings, and conclusions or recommendations expressed in this material are those of the author(s) and do not necessarily reflect the views of the National Science Foundation.

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Part III
mHealth Use and Adoption in Healthcare Delivery

Chapter 9
Understanding Cross-Cultural Requirements in mHealth Design: Findings of a Usability Study of Indian Health Professionals

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9.1 Introduction

Mobile health (mHealth) applications are an increasingly utilized, cost-effective solution for recording, managing, and disseminating medical information. The term mHealth encompasses any mobile device solution used in the practice of medicine and/or public health. Additionally, healthcare informatics is one of the fastest-growing economic sectors in the world today with the potential to make significant impacts to comfort and human longevity. A critical factor in the success of mHealth applications in a global environment rests on the engineering and design of cross-cultural user interfaces to enable the usability, perception, and acceptance of these tools.

Specific to this work, the use of mobile devices for data collection in international public health is gaining prominence for several reasons, namely, portability and ease of use. Using Wi-Fi and other cable-free solutions for network connectivity and cloud computing for data storage and sharing, applications built for mobile devices such as tablets and iPads are becoming increasingly common in the field.

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E. Sezgin et al. (eds.), *Current and Emerging mHealth Technologies*,
https://doi.org/10.1007/978-3-319-73135-3_9

However, moving data collection to new tools can create several user interface challenges, particularly when done in a cross-cultural context. These issues range from the translation of words and expressions to interface layouts and designs. The effects of these deficiencies usually place a cognitive burden on data collectors through a lack of understanding of the interfaces. As a result, data on these questions, particularly with respect to cross-cultural considerations, are lacking.

To enable the successful adoption of these solutions, mHealth developers need to embrace approaches that specifically account for cross-cultural usability. Capturing the complexity and nuances of different cultures in nonfunctional user interface requirements is difficult and, often times, with the lack of a clear understanding, cultural model, and/or established design guidelines for cross-cultural mHealth solutions, mHealth developers will employ their own cultural judgments in application design. This often leads to the design and development of unfamiliar and unusable interfaces for significant, emerging markets.

The goal of this work is to identify the significant cross-cultural factors that affect Indian users' performance of mHealth devices in the international health field. Several research studies have shown the negative consequences of designing interfaces without end-user feedback (Aykin 2004; Badre 2001; Barber 1998; Clemmensen 2012). In most cases, usability studies have been conducted in-house before the deployment of the product to the target audience. Unfortunately, the in-house evaluators might not have similar characteristics and cultural behavior patterns as the target audience (Becker 2002; Becker 2001; Brandon 2001; Chau 2002). As a result, usability gaps are typically created, affecting end-user performance with the target culture.

This paper builds on the previous work by analyzing the qualitative data resulting from the semi-closed and pre- and post-game interviews using a qualitative analysis approach, an adaptation of Strauss and Corbin's grounded theory method (GTM) (Strauss and Corbin 1990). The contribution of this paper is twofold. First, this paper extends the use of GTM as a usability requirements analysis approach for understanding unstructured, qualitative data arising from semi-structured stakeholder interviews. Second, the resulting qualitative analysis indicates that technology familiarity, navigation, language, feedback mechanisms, cognitive overload, and background preferences are significant factors affecting performance and, ultimately, user acceptance. The work presented here is part of a larger effort that (1) investigates how cross-cultural user preferences impact the user interface design requirements of information systems and (2) examines how qualitative analysis approach, like GTM, can contribute to the requirements engineering process.

The remainder of this chapter is organized as follows. Section 9.2 briefly reviews related work in using GTM as a requirements analysis technique. Section 9.3 describes the study's participant design and data collection instruments used in this work. Sections 9.4, 9.5, and 9.6 present the qualitative analysis procedure and a discussion of the results, respectively. Finally, Sect. 9.7 provides some concluding remarks.

9.2 Background Research

This work builds upon two existing lines of research. First, this work extends the utilization of qualitative analysis approaches and a requirements analysis tool to identify cross-cultural factors that might influence usability, accessibility, and interaction challenges of an information system through the discovery and development of nonfunctional requirements. Second, this work contributes to, and further confirms existing results in, the expanding literature on understanding cross-cultural usability aspects for information systems analysis and development and, more specifically, the design and development of mHealth applications. This section summarizes applicable research in these areas.

9.2.1 Usability as a Nonfunctional Requirement

Requirements elicitation and usability studies typically yield large amounts of unstructured, qualitative data that needs to be analyzed, validated, and modeled. In this work, we use a process from earlier work (Chakraborty et al. 2014; Rosasco and Dehlinger 2011) by systematically analyzing the qualitative data resulting from the semi-closed and pre- and post-game interviews using an adaptation of Strauss and Corbin's grounded theory method (GTM) (Strauss and Corbin 1990). This qualitative analysis approach utilizes a three-step coding process through which the researcher can extract common themes from unstructured data originating from multiple stakeholders. Specifically, our adaptation of the GTM qualitative analysis approach analyzes the qualitative text, such as the interview transcripts gathered in the usability study in this work, and develops software engineering artifacts based on user feedback and evaluation. In this case, the specific outcome recommendations generated through the analysis point to specific stakeholder input and output factors that would affect overall user usability, performance, and acceptance of the study participants. These nonfunctional outcomes derived through the qualitative analysis process are in line with factors affecting user performance in similar cross-cultural studies (Chakraborty 2009; Chakraborty and Norcio 2009; Del Galdo 1996).

Software engineering and human-computer interaction (HCI) research has long been interested in developing better approaches and understanding of designing, developing, and validating applications that incorporate the cross-cultural nonfunctional requirements, primarily focused on user interface (UI) design, intended for international, culturally diverse markets and recognizes that application acceptance hinges on positive user experiences (Nielsen 1990). Much of the focus of this research examined cross-cultural requirements, such as language, color choices, layout, etc., that can significantly influence user acceptance, perception, and usability.

Within software engineering, cross-cultural, nonfunctional requirements have been modeled using aspects of the nonfunctional requirement (NFR) framework (Mylopoulos et al. 1999). For example, (Chakraborty et al. 2014) adapt the NFR framework goal trees to facilitate the analysis of expressed softgoals, starting with *usability*, and refine the goal with stakeholder concerns related to usability until they are operationalizable.

9.2.2 User Interface Studies and Public Health

The field of international public health is heavily dependent on accurate and efficient data collection from various fields of operation (Yager et al. 2006). The data input must be easy, and information must remain portable and readable in order to analyze and report significant findings (Friede et al. 1995). Traditional data collection methods, such as pen and paper, although still quite common and are easily accessed with minimal training, increasingly are being replaced with electronic data-gathering tools and applications. The efficacy of electronic data collection has been studied through various research efforts. However, limited empirical work has been carried out in the public health domain to understand the cross-cultural effects of designing a user interface (UI) for a foreign target audience (Plocher and Choong 2012; Plocher 1999).

Several empirical studies in the software engineering domain have reported the value of using a user-centered design approach to UI design for an international audience (Chakraborty 2009; Chakraborty et al. 2009; Chakraborty 2015; Hogan 2004; Plocher and Choong 2012; Stewart 2008). Mobile applications designed for the healthcare field have been tested with end users from different domains of expertise as well as different national and cultural backgrounds. However, very few cross-cultural studies have been carried out to study the effects of UI design on data collection efforts in the field of international public health (German et al. 2001). The limitations of tools designed without feedback from target end users (or data collectors in this instance) can be quite stark (Kersten 2002).

This work builds upon the existing cross-cultural literature, specifically in the context of the mHealth sector, and utilizes GTM as the requirements analysis approach to understand the user preferences and cross-cultural, nonfunctional requirements of Indian stakeholders for a specific mHealth application.

9.3 Study Design

In order to explore these limitations of in-house design, we approached an international public health study underway. Investigators from The Johns Hopkins School of International Public Health (IPH) were investigating Road Traffic Injury Prevention in two Indian cities, Vishakhapatnam and Hyderabad. The team had

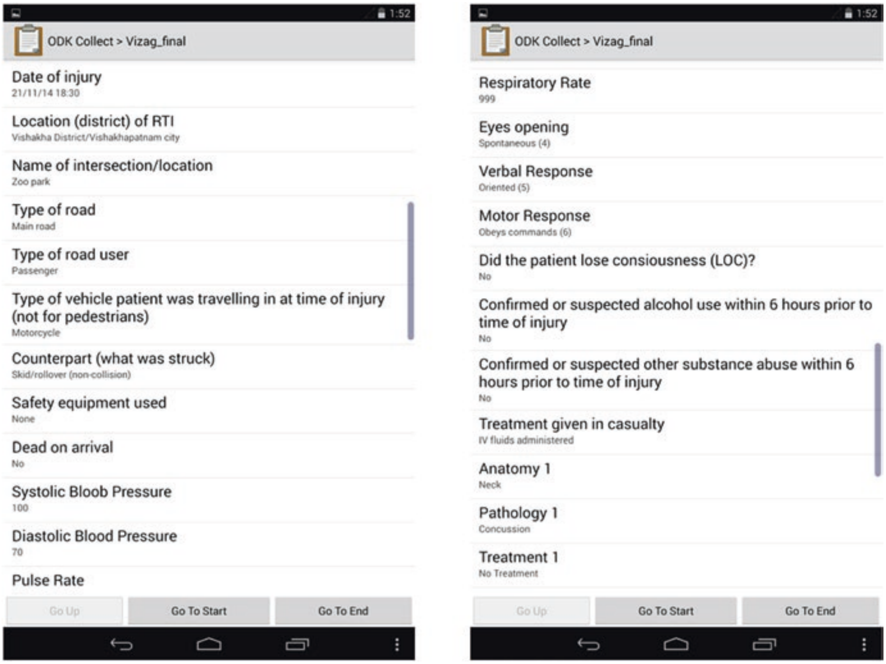

Fig. 9.1 Road traffic injury mHealth application

recently switched over from a paper-based data collection system to an electronic data collection mHealth application, shown in Fig. 9.1. The mHealth application was developed using requirements outlined by the principal investigators of the US-based IPH team. The IPH investigators outlined database requirements for the back-end storage and networking requirements for moving the data. The investigators did not have any specific requirements for the user interface (UI). The design and layout of the UI were left to the development team. The application was developed in-house and loaded onto eight Samsung Tablets and functionally tested using the members of the IPH team in the United States before being shipped to India.

The IPH investigators hired a local team of eight English-speaking, Indian data collectors, who had earned a bachelor's degree or higher from an English-medium institution, to conduct data collection at two major hospital emergency rooms in Vishakhapatnam and Hyderabad, India. This team of eight data collectors was hired and trained to use this English-based mHealth application written by a US-based development team.

The data collectors, whose experience was limited to mobile phones, were trained for approximately 1 month with the IPH team on the use of the device as a part of the overall data collection process. The eight collectors participating in the study were all male and aged 18–35. Before they were interviewed, all had been using the mHealth data collection tool for approximately 6 months.

9.4 Data Collection

In order to gather end-user experience data of the application developed at Johns Hopkins University, we designed an interview questionnaire and sought permission from the Institutional Review Board for permission to speak to the data collectors. Closed interviews of the eight Indian data collectors participating in the Road Traffic Injury Prevention program at Johns Hopkins University were conducted in person by the Principal Investigator in Vishakhapatnam and Hyderabad, India.

The interview data with the Indian data collectors was conducted at the local workplace in India over the course of 1 day. Each interview lasted approximately 1.5 h and was conducted in English. Each participant was informed about the study, and upon consenting, user preference data was collected. The interviews consisted of a closed interview of 25 questions as follows: seven initial, background questions to understand the participant's familiarity and acceptance of mobile devices/applications and 18 questions specifically asking about the mHealth application developed for this study. The 18 questions related to the study are as follows:

1. Before using this new tool, what were your expectations?
2. How did you cope with the new tool?
3. What made the screens easy for you?
4. What was difficult about the screens?
5. What was the most important quality aspect of this new tool?
6. How did you navigate between screens? Was this easy?
7. How can the navigation be improved?
8. Was the layout of the screens easy to read and understand?
9. How can the layout be improved?
10. What are the differences between the paper-based and the mobile tools?
11. Were there any screens that were not used?
12. Was it easy to figure out where to enter data?
13. Compared to the paper-based method, approximately how long does it take to collect data from a patient using this tool?
14. Is the background appropriate?
15. Would you suggest any changes to the background?
16. Are you familiar with the language used in the tool?
17. Would you suggest any changes to the language?
18. Can you suggest ways to improve the tool?

These questions were developed by the investigators after consultation with the project sponsors at Johns Hopkins Bloomberg School of Public Health. The objective was to better understand the target users, the data collectors in the site of the study, and the functions that they were carrying out. All interviews were recorded and transcribed for the analysis. A subset of the interview questions, and representative answers, are provided in Table 9.1.

Table 9.1 Representative open codes from conducted interviews

Interview excerpts	Generated open code(s) with memo(s)
Question: Before using this new tool, what were your expectations? Answer/observation: Firstly, I was a bit excited about the tablet. Would it be possible to use the tablet in the hospital? How would patients react? I was worried about that	Technology adoption; technology acceptance, the subject expresses interest/willingness in adopting the application; patient acceptance, the subject expresses concern about the patient perception of adopting the application as a technology; this concern may indicate obstacles to adoption and allude to privacy concerns
Question: How did you navigate between screens? Was this easy? Answer/observation: Sliding; we first opened the form, sliding to a blank form and the fill in the option. We managed to fill the form the first few times, but it took time. We filled wrong forms. It was hard at first. After that, I bought a smart phone and got practice	Slide/swipe navigation; learnability; learning curve, the subject expresses some initial difficulty in using swipe navigation and seems to indicate unfamiliarity with this method of navigation in mobile applications; unexpected behavior, the subject indicates some frustration in the initial learning curve of the navigation and filling out the forms within the application and mentions that the wrong forms were filled out, indicating an incorrect mental model
Question: How can the navigation be improved? Answer/observation: If they use touch screen it will be easy. They need practice. No other suggestion (smiling)	Touchscreen familiarity; navigation familiarity; learnability, the subject expresses a preference to a touchscreen-based navigation, rather than slide/swipe-based navigation; it is unclear how this is different and seems to indicate unfamiliarity with this method of navigation in mobile applications; self-efficacy, the subject's expressed difficulty and a need for practice with slide/swipe navigation indicates a somewhat lack of mobile technology/application familiarity and the lack of self-efficacy
Question: Was the layout of the screens easy to read and understand? Answer/observation: Head action- layout was easy; sufficient spacing. Generally happy with the overall layout	Layout white space; enabler; readability; understandability, the subject indicates that the user interface layout and the utilized white space were an enabler for learning to use the application and the overall readability and understandability of the application
Question: Can you suggest ways to improve the tool? Answer/observation: Like uh... Make the tool available in other languages. Reducing the number of screens to swipe. After sending the form to server, we cannot make changes. For at least 10 days tools should be monitored for correct usage. What are common columns? They are leaving. Some form of response from the server regarding incorrect data. The tool should generate the own primary key	Language localization; customization, the subject suggests language localization/customization to enable users to select their language preference; reduce slide/swipe navigation, the subject expresses some initial difficulty in using swipe navigation and seems to indicate unfamiliarity with this method of navigation in mobile applications and suggests to reduce the reliance on swipe navigation by reducing the number of screens; data editing; data validation; data feedback, the subject suggests to include some feedback indicating data validation/submission; mental model, the expressed desire for some data feedback indicates that the subject's mental model doesn't match the current application

9.5 Analysis Procedure

The interview data consisted of the observation notes and interview transcripts derived from the interviews with the eight data collectors that were involved in the traffic injury study being carried out as a part of the larger study. Our team sought and received permission to interview all eight end users in the study working in both locations, Vishakhapatnam and Hyderabad.

This research utilizes qualitative analysis elements from (Chakraborty and Dehlinger 2009; Chakraborty et al. 2012) for data analysis. Specifically, this work adopts parts of the approach in (Chakraborty and Dehlinger 2009; Chakraborty et al. 2012), which defines a procedure for analyzing and specifying nonfunctional requirements (NFR) using analytical techniques from grounded theory method (GTM) (Strauss and Corbin 1990), an established qualitative research method (Lazar et al. 2010) Usability, and cross-cultural requirements, represents a key nonfunctional requirement category. Thus, with the qualitative data collected from the interviews, the qualitative analysis procedures were used as requirements analysis tool to identify cross-cultural factors that might influence usability, accessibility, and interaction challenges and affect mHealth acceptance.

The initial analysis procedure uses the analysis steps prescribed in GTM to make sense of unstructured qualitative data (Strauss and Corbin 1990). These steps enable the analyst to deconstruct the unstructured text and reconstruct a summative descriptive theory from it. Specifically, the analytic phases that are being followed in this research are as follows:

- *Open coding*: This phase guides the researcher(s) in partitioning the unstructured, qualitative text into coarse granular concepts and then develops a description of the system in terms of these concepts. These concepts may be derived inductively and represent the researcher's interpretive labeling of text clusters within the unstructured data or could be based on knowledge domain understanding (e.g., usability best practices, nonfunctional categories, etc.). The open coding process typically includes guidance for combining the identified concepts into higher-level categories (i.e., categories consist of similar, grouped concepts).
- *Axial coding*: This phase guides the researcher(s) to take the resulting high-level categories, from the open coding phase, and develop loosely related, hierarchical clusters of categories and concepts to develop a complete understanding of the unstructured, qualitative text through the development of relationships between the identified categories.
- *Selective coding*: This final phase guides the researcher(s) to discover a single, core category, based on the output of axial coding, to synthesize a unifying "storyline" inclusive of the relationships and categories previously discovered.

In addition to the manual coding process, the second element used in this work is the use of a web-based tool, Voyant Tools (Rockwell 2016), that qualitatively analyzes a corpus of text to produce several artifacts: a wordcloud visualization of the text with the most frequently occurring words, a network graph visualization of the higher-frequency terms that appear in proximity, and a trend line graph visualization of the relative frequencies of terms across interviews, amongst other visualizations to support the process of sensemaking of a large tract of unstructured qualitative text. In this work, we employ this tool in the open and axial coding phases.

This analysis procedure was initially carried out independently by two researchers experienced in applying qualitative analysis to interview transcripts and then combined to produce the results reported in Sects. 9.6 and 9.7.

9.6 Findings

The application of the grounded theory method (GTM) (Strauss and Corbin 1990), described in Sect. 9.5, and the intermediate findings from each coding phase are described in this section.

9.6.1 Open Coding

During the open coding stage, the input, unstructured qualitative interview transcripts were independently analyzed line by line by the researchers to identify key ideas and concepts related to the user's interaction with the mHealth application and to their perception of its usability. These key ideas and concepts represent the open codes and are accompanied by explanatory memos related to their meaning. Throughout the open coding process, the researchers partake in the constant comparison between text excerpts within and across interviews, to ensure consistency of labeling, interpretation, and memoing. Table 9.1 provides an illustrative example of the intermediary findings resulting from the researchers combining open codes and memos that were generated during the process.

The process for identification of key ideas/concepts through open coding is carried out until the observations and interview responses for all the participants are coded. Once this process is completed and reconciled amongst the researchers, the next step of open coding is to identify preliminary relationships between the open codes that were identified in the previous step. The diagrams (loosely based on Euler diagrammatic notation) are used here to facilitate the analysis, based on the procedural guidelines from (Chakraborty et al. 2012). These are shown in Fig. 9.2.

The initial open coding, partly shown in Table 9.1, indicated several enablers and inhibitors to the ease of use, and ultimately acceptance, of the mHealth application. As an illustrative example, open coding analysis (shown in Table 9.1) of the interview question "Can you suggest ways to improve the tool?" across all interview participants yields nine concepts that emerged from the data: language localization, customization, reduce slide/swipe navigation, data editing, data validation, data

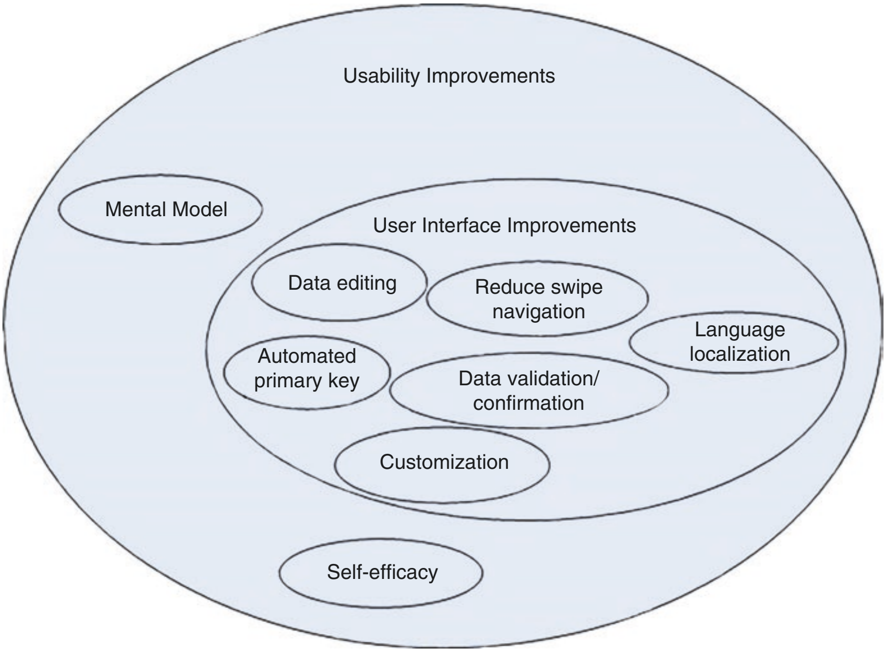

Fig. 9.2 Representative cluster diagram derived from open codes

feedback, mental model, automated primary key, and self-efficacy. These concepts fall into two broad categories describing aspects to improve the usability of the mHealth application: operationalizable requirements to improve the usability (e.g., improvements in localization/customization, improvements in navigation and data entry/editing) and training/user acceptance hurdles (e.g., mental model and self-efficacy). Figure 9.2 provides a sample of the cluster diagram resulting from the open coding analysis.

9.6.2 Axial Coding

Informed by the open coding stage, the NFR framework can be used as a semiformal, structured notation during axial coding for "representing and recording the design and reasoning process" relating to the discovery and analysis of NFRs (Mylopoulos et al. 1999). NFRs are treated as softgoals that need to be clarified, disambiguated, elaborated upon, and operationalized, if the proposed system has to incorporate the appropriate quality attributes (Mylopoulos et al. 1999). To do so, the NFR framework suggests the development of a softgoal interdependency graph (SIG) representing the identified NFRs and then systematically decomposing the softgoals into sub-softgoals. This decomposition is continued until sufficient refinement is achieved to allow the systems analyst to understand the possible solution alternatives, and their dependencies, that can be adopted to meet the softgoals.

During the axial coding phase, the developed categories and concept clusters are further examined to consolidate the qualitative data further and develop a further understanding of the relationships between open codes and to discover the overall themes emerging from the qualitative interview data. The input to this coding state is a cluster diagram (see Fig. 9.2), and the output is an artifact that describes the relationships amongst different categories, subcategories, and properties.

In this work, the focus was on the development and refinement of the uncovered, nonfunctional properties necessary to support this mHealth mobile application and understand any underlying cross-cultural requirements. Specifically, the desired *goal* to be achieved, in this case, is *usability*. In NFR framework terms, "usability" represents the highest-level softgoal that then needs to be systematically decomposed in a top-down approach into its comprising subgoals that, if satisfied, would lead to the satisfying of the root-node goal. Specifically, the top-down decomposition of softgoals relies on a process of inspection and comparison of the various subcategories and their properties through the identification of which subcategory potentially contributes/inhibits to the objectives of another subcategory; this oftentimes necessitates re-engaging with the original source qualitative interview data to confirm perceived relationships amongst categories and concepts. This process of decomposition and refinement continues until each branch of the goal tree terminates in a leaf that can be construed as an explicit operationalization of its parent softgoal or until the qualitative data is exhausted.

Using the category cluster diagram developed from the interview data, a qualitative analysis web application tool, Voyant Tools (Rockwell 2016), was utilized to assist in reexamining the developed concepts and categories in the context of the original source data. To do so, Voyant Tools' keyword in context visualization to consult the original text with each of the open codes was previously developed. As an illustrative example, Fig. 9.3 depicts the tool's visualization for the open codes *background*, *feedback*, *search*, *layout*, and *background* and displays the context text in which these terms occurred in the original source text.

Further, in order to develop the relationships and construct a hierarchy of concepts and categories, as the axial coding phase prescribes, and to deconstruct the softgoals into subgoals, as the NFR framework's SIG construction prescribes, Voyant Tools' network visualization was utilized to understand how identified open codes are related to other identified concepts and categories. As an illustrative example, Fig. 9.4 showed the tool's visualization for the open codes *easy* and *background* and highlighted in bold with the relationships to other open codes. For example, the figure on the top illustrates the network of open codes that enables (i.e., that which the participants easy to use/understand) usability. Similarly, the figure on the bottom illustrates the relationship of open codes with the background concept to other open codes.

A representative SIG developed from the category cluster diagrams using the qualitative analysis tool is shown in Fig. 9.5 and illustrates the subgoals, derived through qualitative analysis of the interview text, of the deficient cross-cultural, user

Left	Term	Right
15 minutes 14. White color	background	with black color letters would
on the device- after exploring.	feedback	- good working and sounds would
It made it easier to	search	for forms 6. Sliding; we
No other suggestion(smiling) 8.	layout	was easy sufficient spacing. Generally
spacing. Generally happy with overall	layout	9. layout was ok. No
happy with overall layout 9.	layout	was ok. No improvement needed
15 minutes 14. White color	background	with black color letters would
would be good. Or blue	background	on black letter 15. Somewhat
learn because of non-medical	background	. After a bit of learning
tablet 7 min 13. White	background	with black writing 14. Red
ability to silence device(control	feedback	mechanisms especially during meetings) 1
for tablet 14. I changed	background	setting to blue and black
As per my experience, the	layout	is good enough 10. Tablet

Fig. 9.3 Representative keywords in context from open codes

preference, design requirements in the development mHealth mobile application. The implications of this resulting SIG and qualitative analysis results are provided in the next section.

9.7 Discussion

The analysis of the findings in the development of the SIGs identified several significant areas of design improvement that have the potential to affect user performance of the Indian data collectors. Amongst these are:

- Technology familiarity
- Language challenges
- Navigation/searchability
- Cognitive overload while inputting data
- Feedback
- Background layout

Technology familiarity and language challenges The familiarity with the technology and language challenges are in line with the literature. Most end users have a degree of apprehension with new technologies and languages to which they are unaccustomed. Several studies have shown that this can affect user performance, especially in cultures with high degrees of collectivism and power distance (Choi 2005; Clemmensen 2012; Hofstede 1991). In these cultures, committing errors is akin to losing face or dignity, and as such most users would not complain about this flaw.

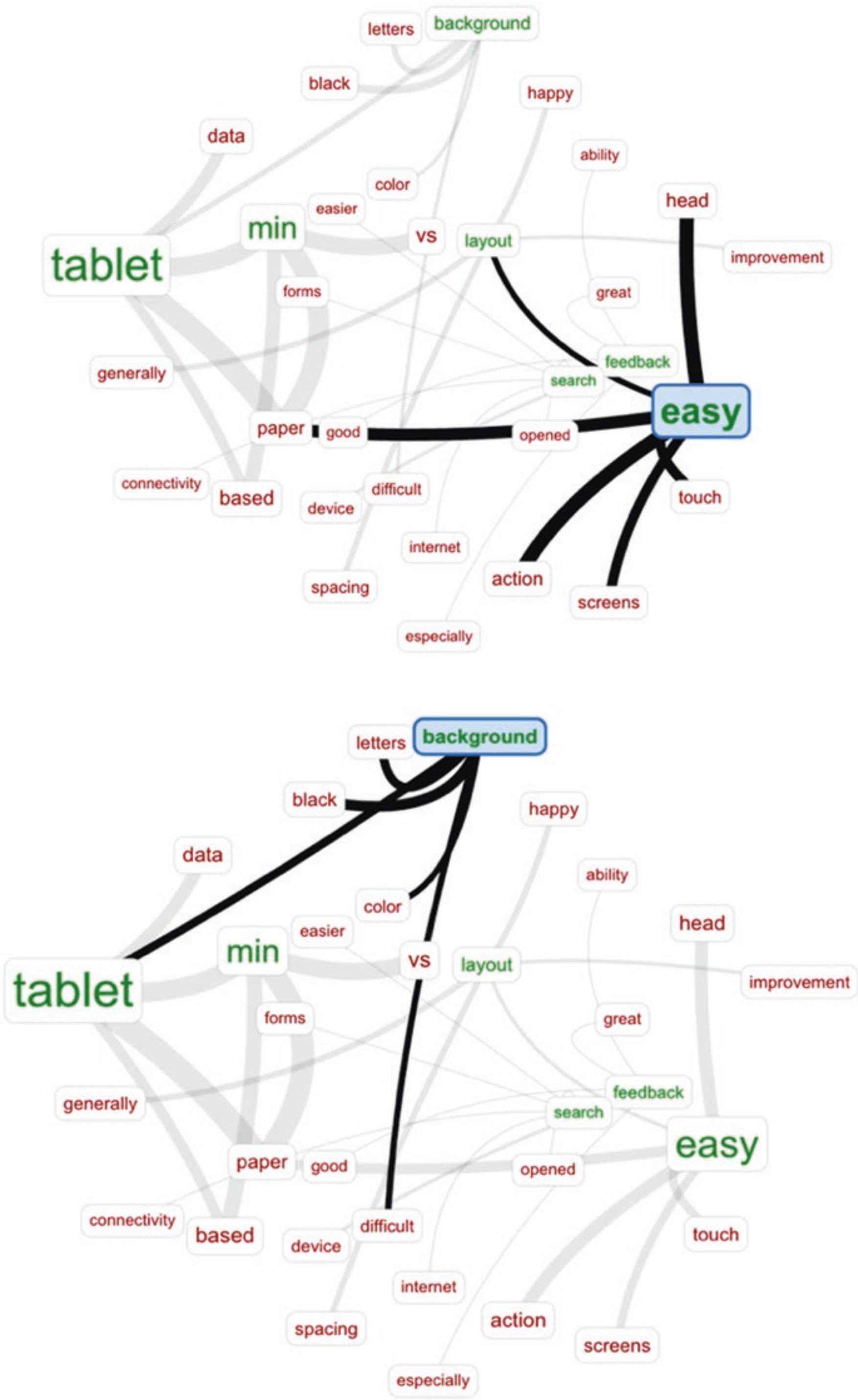

Fig. 9.4 Representative network visualizations from open codes

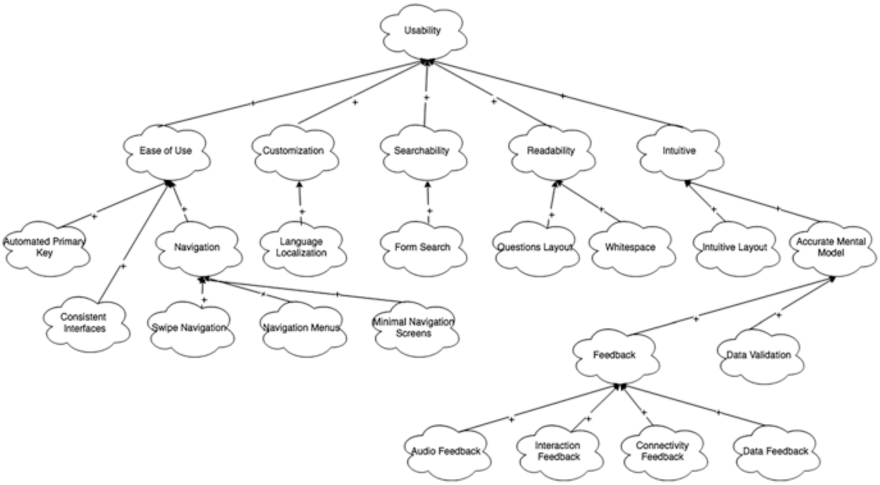

Fig. 9.5 Representative softgoal interdependency graph

Navigation/Searchability and Cognitive Overload The analysis revealed significant challenges with the overall layout of the application as it related to navigation and cognitive overload while inputting data. As these mHealth tools were handheld devices, inputting data or navigating screens on large scales can be difficult. Several studies have shown similar findings (Day 2005; Evers 2000). Indian cultures tend toward high levels of uncertainty avoidance; this results in participants who are unlikely to venture beyond the tried and tested to find more efficient methods of navigation or search (Hofstede 1991).

Feedback and Background Layout Several participants had indicated cognitive difficulties with the lack of feedback mechanisms, such as audio or haptic feedback, to task completion and background colors. This simply ends user preference based on cultured learning behavior. This is also consistent with several findings (Del Galdo 1996; Hogan 2004; Kersten 2002). The participants in this study were all educated and had indicated interacting with smart mobile phones for several years. Based on their conditioned behavior, it is reasonable to expect end-user preferences that would affect user performance.

The outcomes from this study must be placed in the context of this public health study. Public health professionals of varied backgrounds and experiences that are involved in other data collection efforts might indicate dissimilar user experiences. Our cross-cultural findings are based on a data-gathering tool that was designed in the United States and applied in India only. Our findings cannot necessarily be generalized to other cross-cultural design efforts. However, the findings in our study are certainly consistent with other similar empirical study findings (Chakraborty 2009; Stewart 2008).

9.8 Conclusion

A critical factor in the success of mHealth applications rests on the design of user-friendly, cross-cultural interfaces to enable the usability, accessibility, perception, and acceptance of the mHealth applications in international markets. To enable the successful adoption of mHealth solutions, mHealth developers need to embrace approaches that specifically account for cross-cultural usability. Capturing the complexity and nuances of different cultures in nonfunctional user interface requirements is difficult, and, often times, with the lack of a clear understanding, cultural model, and/or established design guidelines for cross-cultural mHealth solutions, mHealth developers will employ their own cultural judgments in application design. To investigate how cross-cultural user preferences impact the user interface design requirements of information systems through employing a qualitative analysis approach, this paper confirms previous research by finding that participants' familiarity with technology, ability to localize/customize an mHealth application's language, and reducing the required cognitive overload of required input data and mental model mode of navigation contribute to improving usability and, eventually, application acceptance.

Acknowledgments This study was conducted as part of the evaluation of the Global Road Safety Program conducted by Johns Hopkins International Injury Unit (JH-IIRU) and was funded by the Bloomberg Philanthropies.

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Chapter 10
Intention vs. Perception: Understanding the Differences in Physicians' Attitudes Toward Mobile Health Applications

Emre Sezgin, Sevgi Özkan Yildirim, and Soner Yildirim

10.1 Introduction

Mobile health (mHealth) has becoming a significant element for healthcare delivery. As such, the investments and researches on mHealth have been rapidly increasing. A number of international associations pointed out the growing market of healthcare services with the digital era, and most of them anticipated the growth in telemedicine and remote healthcare services in high numbers for the following decades. McKinsey's report in 2015 underlined that mobile device (tablet and smartphone) market may expand 1.1–1.3 times by 2018. The value created by the expansion may reach to hundreds of billions of dollars, and this growth will affect health and medical services the most (Atluri et al. 2015). On the other side, the 2015 OECD Digital Economy Outlook report presented that "the global mHealth market may reach $23 billion in 2017, with Europe accounting for $6.9 billion and Asia-Pacific for $6.8 billion, ahead of the North American market of $ 6.5 billion" (OECD 2015). The growth was not only triggered the investments but also the reduction of the costs of healthcare delivery. By 2017, mHealth use in the European Union was reported to have potential to save €99 billion in healthcare spending (OECD 2015). Furthermore, global reports presented that in 2025, the use of the mobile Internet, as well as applications, was estimated to have an economic impact around 3.7–10.8 trillion dollars

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E. Sezgin et al. (eds.), *Current and Emerging mHealth Technologies*,
https://doi.org/10.1007/978-3-319-73135-3_10

per year (Manyika et al. 2013). For instance, potential value gain was estimated to be 10–20% cost reduction only in chronic disease treatment via telemedicine. Considering the current developments and estimations, the worldwide dissemination and use of mobile health technologies have constantly been increasing. Similarly, use of mobile technologies and applications by healthcare providers has also increased (PwC Health Research Institute 2014; Ventola 2014). In that regard, the mobile application markets (App Stores) presented over thousands of applications related to healthcare services that are used for checking tests, keeping records, and taking assistance in diagnoses. These applications aimed to assist physicians or patients to manage and maintain healthcare-related data by enabling storing, recording, and accessing information (Hao et al. 2013; Martínez-Pérez et al. 2013).

On the other side, these reports demonstrated that the mHealth technologies have penetrated to many different segments, and they have been offered to different user groups in the market (e.g., patients, physicians, nurses). These groups were expected to use mHealth applications in checking, controlling, and maintaining personal healthcare or to deliver the services. However, it should be noted that the success of these technologies does not solely depend on the technological innovations itself. The perceptions about mHealth and the intention to use these new technologies are important elements in order to utilize them in practice effectively. In that regard, not only the mHealth users' intentions but also the perception of potential users should be considered, and the assessment of user behavior is an important input for the success of mHealth use.

10.1.1 Background Information on Assessment

Individuals' behaviors and attitudes toward information technologies have been investigated for a long time (King and He 2006; Rondan-Cataluña et al. 2015). The concept was employed for assessment of technology acceptance in the early 1990s, and the studies in technology acceptance gained interests (Davis 1989; Wood and Bandura 1989; Ajzen 1991; Venkatesh and Davis 2000; Venkatesh et al. 2003). One of the leading theories was proposed by Davis (1989) as the technology acceptance model (TAM). TAM is used to determine factors influencing behaviors of users toward technolo gies. The model argues that the actual use of technologies is influenced by perceived ease of use (PEOU) and perceived usefulness (PU). Thus, PEOU and PU were main contributors to individuals' attitude and behavioral intention (BI). In the latter studies, TAM has been modified involving other constructs to assess effects of different factors about different technologies (Bagozzi and Warshaw 1992; Venkatesh and Davis 2000). In the literature, there have been a number of studies about the healthcare technologies successfully using TAM theory (Holden and Karsh 2010). Furthermore, the studies employed an integrated or modified TAM to keep up with changing user needs and healthcare technologies. However, a major drawback of TAM was pointed out as the difficulty in the generalization of results and inconsistency in relationships between constructs (Venkatesh et al. 2003; Legris et al. 2003; Sun and Zhang 2006). Following TAM, the unified theory of acceptance and use of technology (UTAUT) was proposed as a new integrated theory, which aims to assess the likelihood of success of new technologies and determine drivers of acceptance (Venkatesh et al. 2003). In 2012, Venkatesh, Thong, and Xu (2012) proposed UTAUT 2, which was an updated UTAUT including hedonic motivation, price value, and habit as additional exogenous variables influencing behavioral intention. Similar to TAM, UTAUT has been successfully implemented in a number of studies (Schaper and Pervan 2007b; Chang et al. 2007; Aggelidis and Chatzoglou 2009; Kijsanayotin et al. 2009; Pynoo et al. 2012; Dünnebeil et al. 2012). In addition to that, the theory of planned behavior (TPB) and innovation diffusion theory (IDT) have also been used in behavioral researches in healthcare delivery (Sezgin and Özkan-Yildirim 2014).

10.1.2 Aim of the Study

This chapter investigated the intentions and perceptions of physicians toward mHealth applications considering two different perspectives of physicians. In that regard, following a secondary research methodology, findings of previous researches about mHealth application use and adoption were employed to provide a comparison between two physician groups. Authors believe this comparison would be a valuable asset providing a distinct overview, which would be used in planning new health application development, management, and promotion.

10.2 Methodology

The chapter employed a secondary research method, which focuses on the synthesis of previous researches (Sezgin et al. 2017; Sezgin et al. 2016). In order to provide a comparative overview, the findings of these researches were discussed revealing the similarities and differences in mHealth application adoption by two user groups. The detailed methodology and research procedure of these researches were given in this section.

The researches that were held in this study were reported findings for intentions and perceptions toward mHealth application by the user and nonuser physicians. In these researches, similar research and testing procedures were employed which helped to present a common ground for the comparison. In both researches, to understand the influencing factors to use mHealth apps, a systematic method was followed. At the first phase, a literature research was conducted to identify researches about mHealth. It also helped to understand the behavioral theories in the domain as well as to gather constructs for assessing adoption and acceptance of mobile health information systems by the physicians. Following that, the conceptual model was developed, and hypotheses were formulated. In both researches, the same model was used, and the data collection was completed by employing a structured survey (questionnaire). Convenience sampling was used as the data collection method, and

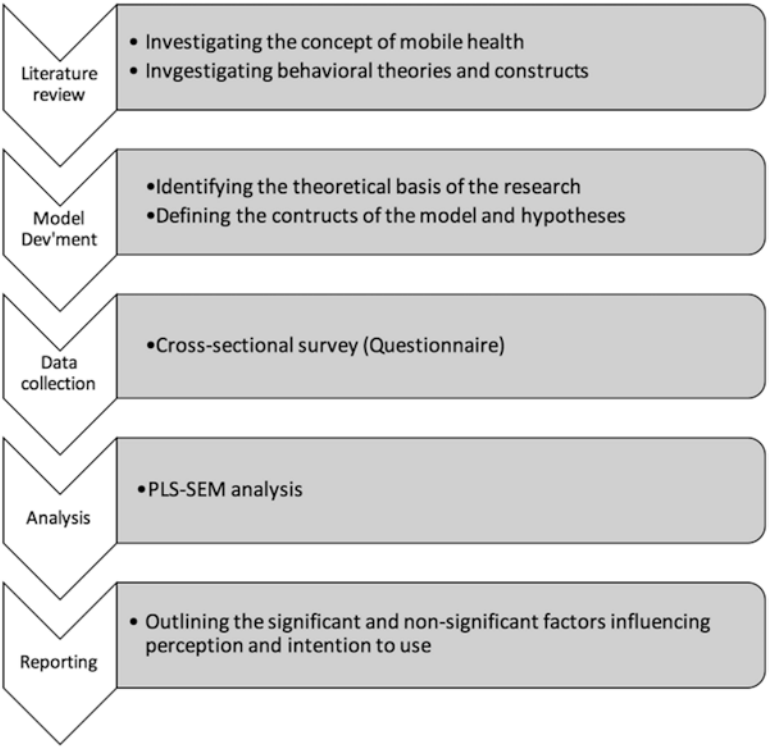

Fig. 10.1 Flow of the research processes

an online survey tool was employed. Non-mHealth application user physicians (n = 122) and mHealth application user physicians (n = 137) participated in the survey. Confirmatory factor analysis and structural equation modeling (SEM) were used in the analysis of quantitative data. Figure 10.1 provided an outline of the research processes.

The following constructs were used in the model, and they were tested in both researches in order to understand perception (of nonusers) and intention (of users) toward mHealth applications.

- Behavioral intention (BI): The act of deciding to use a particular technology (Venkatesh et al. 2003).
- Performance expectancy (PE): Personal beliefs using technology would increase the job performance (Venkatesh et al. 2003).
- Effort expectancy (EE): Personal beliefs using technology would be free of effort (Venkatesh et al. 2003).
- Compatibility (CO): The perception about the use of technology is consistent with users' needs, experiences, and values (Rogers 1995).
- Mobile self-efficacy (MS): Perceptions about personal abilities to use the technology to fulfill healthcare task and duties on mobile devices (Schaper and Pervan 2007b).

- Technical support and training (TT): The perception and the need for support and training to gain knowledge about the technology (Venkatesh et al. 2003).
- Perceived service availability (PS): The perception about the technology which is able to support "pervasive and timely usage" (Venkatesh et al. 2003).
- Personal innovativeness in IT (PI): The state of a person's willingness to take a risk in trying a new technology or innovation (Agarwal and Prasad 1998).
- Social influence (SI): The degree of social perceptions about technology's desirability (Venkatesh et al. 2003).
- Mobile anxiety (MA): The apprehension when using or having the possibility to use mobile devices and applications (Schaper and Pervan 2007b).
- Result demonstrability (RD): Tangibility or the level of observability of the results in using technology (Venkatesh and Davis 2000).
- Habit (HB): Repetitiveness and routine act of behavior in using the technology (Gagnon et al. 2003).

10.3 Comparison of User and Nonuser Physicians

In this section, the significant and nonsignificant factors of mHealth application use were outlined. Figures 10.2 and 10.3 presented the research model used for each group outlining significant (continuous line) and nonsignificant (dashed line) relationships. Research model testing resulted differently for each group regarding significant relations as well as the implications. In this section, a comparison of factors influencing these different groups was given.

Significant and nonsignificant relationships for both groups were given in Table 10.1. The researches reported that PE and PI influenced BI for users and EE and TT influenced BI for nonusers. This finding revealed that mHealth application user physicians would perceive their job performance and their willingness to try new technologies influential their intention to use mHealth applications (Chau and Hu 2002). On the other side, the perception of nonusers depended on the ease of using mHealth, and the support they were receiving would affect their intention to use mHealth applications (Chang et al. 2007).

The behavioral intention was influenced by perceived service availability and mobile anxiety in both groups. Thus, there was a common perception regarding reachable and accessible mHealth applications in practice (Becker et al. 2014). Furthermore, compatibility influenced performance expectancy, and mobile self-efficacy influences effort expectancy for both groups. Here, job performance was perceived to be related to compatible systems by nonusers similar to users, such as mHealth with hospital systems. In addition to that, the ease of mHealth use was perceived to be related with personal competency for both groups. However, their indirect influence on behavioral intention can be observed differently in each group due to the significant impact of PE and EE. Thus, compatibility was rather influential on BI over PE for user physicians, and mobile self-efficacy was on BI over EE for

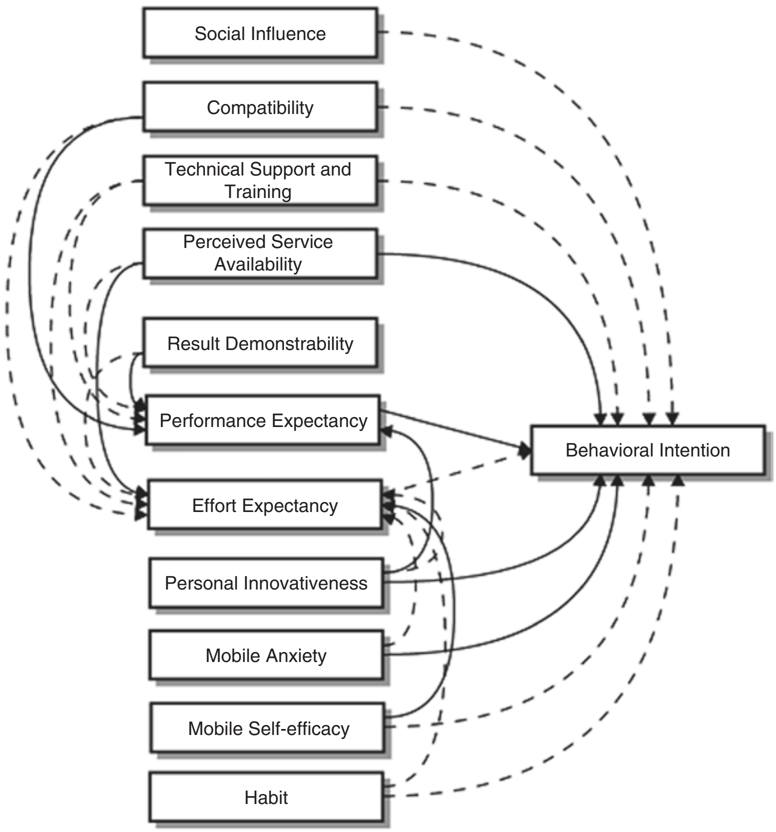

Fig. 10.2 Research model for mHealth user physicians

nonusers. That impact would be related to perceived job performance of user physicians since they observe the relation of compatibility and job performance. For nonusers, the expected ease of using mHealth applications could be perceived to be related to personal competency (Schaper and Pervan 2007a).

On the other side, the direct effect of CO, HB, MS, and SI was not influential on BI for both groups. Here, there was a consensus of physicians about direct impact on BI. Even though CO and MS had an indirect effect, they were not perceived to have a significant influence on BI as well as HB and SI. As explained in the previous section, these factors might have seen rather less relevant or non-applicable by the physicians considering the current state of mHealth application use in health institutions (Gagnon et al. 2015).

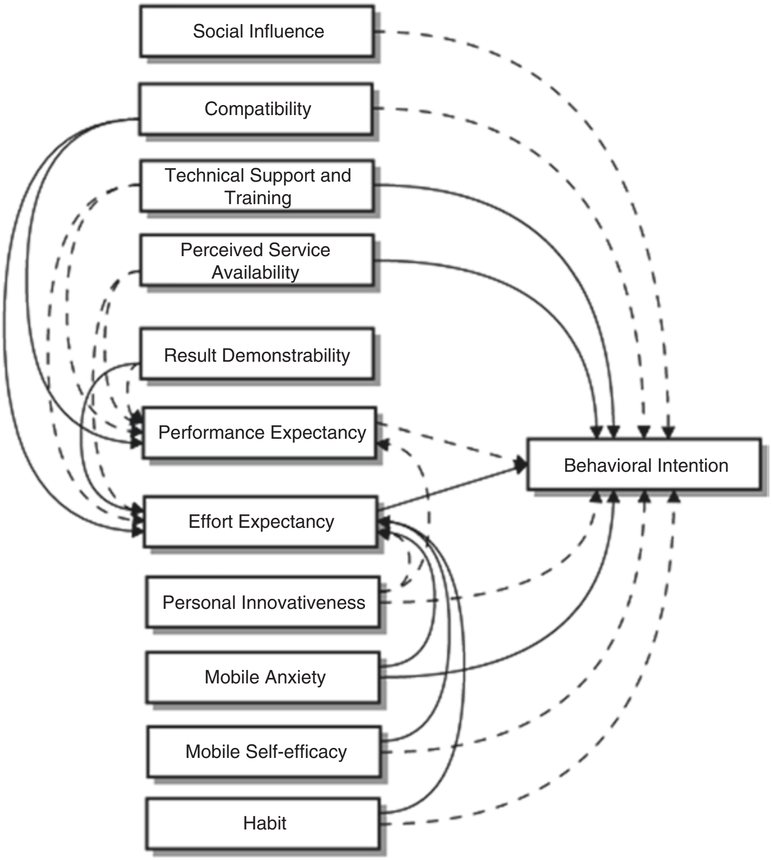

Fig. 10.3 Research model for nonuser physician

10.4 Suggestions

The previous section outlined the findings of intention and perception to use mHealth applications and implications. Considering both groups, in this section, a number of elements were outlined in order to be considered in application development and managerial processes in the common ground. Becker et al. (2014) provided psychological, clinical, technological, and regulatory viewpoints to outline the state of the mHealth. In this section, these viewpoints were used to categorize the elements in suggestions.

Table 10.1 Significant and nonsignificant relations for mHealth user physicians and nonuser physician

	User physicians		Nonuser Physicians	
	Sig.	Non-sig.	Sig.	Non-sig.
PS → BI	✓		✓	
MA → BI	✓		✓	
CO → PE	✓		✓	
MS → EE	✓		✓	
CO → BI		X		X
HB → BI		X		X
MS → BI		X		X
SI → BI		X		X
PI →EE		X		X
PS → EE		X		X
TT → EE		X		X
TT → PE		X		X
PE → BI	✓			X
PI →BI	✓			X
PI →PE	✓			X
RD → PE	✓			X
PS → EE	✓			X
EE → BI		X	✓	
TT → BI		X	✓	
HB → EE		X	✓	
RD → EE		X	✓	
CO → EE		X	✓	
MA → EE		X	✓	

10.4.1 Psychological Perspective

Today, more than 75% of world population are able to access mobile communication services (Becker et al. 2014). In the largest countries, such as the USA and China, more than 27 thousand medical applications were available on Android and iOS market (Xu and Liu 2015). However, literature provided that mHealth applications were underutilized in practice, and it has created no dramatic change in both organizational culture of health institutions and health behavior (Becker et al. 2014). In that regard, collaboration has been a need among application developers, physicians, and researchers who have expertise in behavior and attitudes. In this study, the significance of perception in job performance, ease of mHealth use, personal perspectives in new technologies, and potential of anxiety were revealed for both groups. Thus, the following elements should be considered for mHealth applications.

Focusing on the job performance and providing simple applications Since the workload is high and quick access to the information is a need, physicians rather prefer less exhausting assistive services in practice. Thus, they expect effort-free and useful, to-the-point applications in healthcare services. The simplicity of the application and providing quick and relevant information are valuable features in use (Gagnon et al. 2015).

Promotional activities for new mHealth applications There is a potential interest of physicians toward new technologies. Utilizing this feature, mHealth applications could be promoted among physicians for encouraging active use and creating a positive perception in healthcare services. Thus, instead of basic training or seminars at the initial stage, the promotional activities, such as meetings or activities including social interactions, would attract both users and potential users toward using mHealth applications in practice. Alternatively, key characters in the organizations, such as "opinion leaders," would be assistive to disseminate the use of mHealth applications, which would also impact the organizational culture and mHealth use "etiquette" in the long term (Hao et al. 2013).

The next level training. Following the promotional activities, training would help physicians to use mHealth in completing daily tasks. It could be provided as on-the-job training and in-action implementations. It is especially beneficial for new users in order to eliminate the risk of resistance and reduce potential anxiety in use by familiarizing the new users to the mHealth applications. In addition to that, it would reduce the possible risks as errors in multitasking (Wu et al. 2005; Varshney 2014).

10.4.2 Clinical Perspective

In the current state, literature and the study demonstrated that simple features of mobile technologies work effectively in clinical practice, especially in developing countries, such as communication applications and SMS (Free et al. 2013; Källander et al. 2013; Becker et al. 2014).

Collaboration is the core The study provided that there is a social bond among healthcare providers (i.e., physicians, nurses, technicians). Thus, collaboration among healthcare providers has been a must, and the applications should be developed regarding collaboration of the core of the operations. In that regard, easy sharing methods and collaborative working tools would be beneficial in mHealth applications.

Providing continuous services The service availability was perceived to be an important factor for the physicians. In that regard, one of the major benefits of communication applications was their service availability and providing access to the service time and location independent. Here, the benefits of communication applications could be embraced in a broader extend to include healthcare-specific services providing significant functions available.

10.4.3 Technological Perspective

The study provided that the technological infrastructure of healthcare institutions include the Internet and local area computer network within the institutions. Each hospital uses a medical health record system to keep the track and to report the operations. In that regard, a couple of issues should be considered for mHealth application use.

Compatibility and interoperability of applications Compatibility of mHealth applications with the healthcare systems would influence physicians' working routines and the job performance as well. The current state of mHealth showed that the technology is still evolving and incompatible mHealth applications exist (Becker et al. 2014). Thus, the development of a mobile-compatible healthcare service platform for institutions is as important as developing mHealth application itself. In addition to that, the communication among the systems is also crucial for services. Interoperable systems would also boost the development and use of mHealth applications in healthcare services.

Providing demonstrable results The ability to demonstrate the medical results, calculations, problems, or processes was perceived important by the physicians. Hence, the mHealth technology being provided should grant the ability to display and share high-quality visual medical contents. In that regard, increasing visual quality as well processing speed in medical contents would be valuable in healthcare delivery.

Focusing on infrastructure Technological infrastructure, especially the communication network, is important for timely delivery of healthcare services (Sezgin and Özkan-Yildirim 2016). However, the reliability could be an issue, and uninterrupted service could not be provided for the developing countries (Varshney 2014). Thus, developing an interoperable and compatible platform does also rely on a reliable infrastructure. It is suggested to develop a contingency plan and ad hoc solution maps for unexpected infrastructural issues (such as electricity cuts, network loss, hardware and software malfunctions).

10.4.4 Regulatory Perspective

Laws and regulations regarding mHealth technologies and applications are at the initial stage (Barton 2012; Becker et al. 2014). In developing countries, it was estimated to adapt the regulations in the long term. In that regard, the following points would be considered in mHealth application development.

Acting with the laws and regulations about mHealth Even though the current state of regulations is in the development phase, the need for laws and regulations is increasing considering the number of available mHealth applications in the market. These applications were commercially available and enabled users to share confidential information with the third parties. Thus, for security and privacy of information, regulatory acts were required by the authorities. In the study, the physicians have also stated their expectations on regulations about mHealth applications.

Standards for applications This study reported that some mHealth applications were following international standards in medical practice while providing content in healthcare. However, the market was crowded with many other unregulated and unstandardized applications being available for the end users. Considering the current trajectory, mHealth applications following the standards were found more reliable by the physicians. Thus, considering international standards in the developmental phase would help to build the reliability and credibility of the mHealth applications. In addition to that, providing the procedures for implementing international standards at national level application development would also be recommended to the authorities.

Considering the four perspectives, the current stage of mHealth would be an opportunity for developers to anticipate the trajectory of the transformation in healthcare services and to release their applications in the market on time. In that regard, the potential of change in organizational culture and its evolution around mHealth applications and technologies should be considered in long-term strategic plans.

10.5 Conclusion

In this chapter, a comparative assessment of mHealth application adoption by the physicians was reported. Considering the intentions and perceptions of physicians, several suggestions were outlined. The suggestions in this chapter would be helpful for better understanding the characteristics of two different groups of physicians. The findings would guide developers and authorities to understand user needs. Thus, it would be a valuable input in the mHealth application and healthcare policy development.

It should be noted that this study has also extended the literature regarding researches investigating users and nonusers' behaviors in healthcare technologies (Cheung et al. 2013; Bidmon et al. 2014; Sims et al. 2014). However, further studies, employing qualitative designs, would be resourceful to achieve in-depth understanding in physician intentions and perceptions toward mHealth application use.

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Chapter 11
HealthGuide: A Personalized Mobile Patient Guidance System

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11.1 Introduction

It is accepted by healthcare providers that the use of health-related information technologies (IT) can improve efficiency, quality, patient satisfaction, and access while also reducing healthcare costs (Buntin et al. 2011; Payne et al. 2013). Although advances have occurred in the adoption of Health IT, there are still opportunities and challenges calling for new solutions. One of them is extending the use of mobile health (mHealth) which refers to the application of mobile IT within the healthcare domain. mHealth has the potential to dramatically reduce the costs of healthcare operations while improving healthcare service quality and decision-making processes of professionals and patients, as a result of increasing reachability, accessibility, and ability for effectively performing tasks (Sarker and Wells 2003; Nah et al. 2005). It was estimated that mHealth could represent up to $340 billion in annual healthcare cost savings worldwide by the end of 2016 (SNS Telecom 2016). The global mHealth market is projected to reach $62.84 billion by 2021, growing at a compound annual growth rate (CAGR) of 39.35% during the forecast period of 2016 to 2021 (Intelligence 2016).

mHealth provides a unique opportunity for customization of care for individual patients based on their health requirements and behavioral characteristics. Additionally, it facilitates increased patient engagement by utilizing mobile devices with anytime, anywhere access and multitasking capabilities. The number of studies incorporating individualized solutions has been increasing due to the widespread availability of mobile devices (Chomutare et al. 2011; Simon and Seldon 2012). It is reported that more than 100,000 mHealth applications are currently available for a wide variety of users (Xu and Liu 2015).

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E. Sezgin et al. (eds.), *Current and Emerging mHealth Technologies*,
https://doi.org/10.1007/978-3-319-73135-3_11

Personalized services can be provided in the form of context-aware applications by using smartphones and other mobile devices connected to the Internet. To this end, the enabling set of technologies is explored within the domain of pervasive computing (also called ubiquitous computing), which consists of information processing, communication technology, and computer performance through embedding sensors, actuators, and processors in the environment (Estrin 2002), and also includes the concept of Internet of Things (IoT). It has received immense attention from both academia and industry as part of exploring its promising opportunities, such as the application of context awareness in interaction design. Accordingly, pervasive healthcare (or ubiquitous healthcare) refers to a vision of the future of healthcare for delivering healthcare services with higher quality at lower costs as well as with higher patient experience and satisfaction (Boye 2008).

From the perspective of patients, healthcare-related services are complex to comprehend. While receiving such services, patients typically have to carry out a large number of tasks, both inside and outside the hospital under time limitations and in uncomfortable circumstances. For instance, visiting large hospitals causes difficulties on locating facilities and accessing relevant, personalized information promptly. Indeed, following rather complicated task sequences and moving around while trying to reach various healthcare provider locations may cause difficulties for patients, particularly elderly or those suffering due to a disease. Currently, hospitals are handling this problem by installing help desks to guide patients. As a supplementary solution, an mHealth application utilizing context-aware data supplied by pervasive technologies may be beneficial to guide patients and to help them accomplish their tasks accurately and in the correct order inside and outside the hospital. Patients may be offered timely access to personalized health information, such as a high-level description, time and place of the treatment, navigation information to a facility, and information related to performing tasks associated with the treatment (Tang and Lansky 2005; Collins et al. 2011; Yamin et al. 2011; Giardina et al. 2014). Providing such capabilities represents a potential solution filling the information gap between the patient and health provider and improving the outcome.

Putting mHealth solutions into good use starts with analyzing and proper understanding of the user needs for the targeted application domain. In the context of a mobile guidance system, such needs include providing instructions to patients for their next tasks, informing them about facility locations, and notifying them regarding scheduled appointments, possible delays, or reminders about prescribed medicines. In order to address such needs, workflows have been successfully used as structural models. Accordingly, workflow management systems (WMSs) provide the capabilities for creating and managing workflow executions through the use of the software. In addition, this capability may be supplemented by the utilization of pervasive technologies for collecting and processing real-time data from various devices such as sensors, GPS modules, RFID tags, Bluetooth units, and smartphones, as part of providing context-aware solutions.

These pervasive technologies are embedded in a complex set of other technologies, physical surroundings, people, and procedures that together constitute socio-technical systems. The concept of socio-technical systems was initially mentioned by Emery and Trist (1960). Socio-technical system design (STSD) refers to an approach that considers human, social, and organizational aspects, which include user roles, job change, social interaction, as well as technical aspects, such as hardware, software, work process, workflows, information management, data structures, and related technical knowledge. The STSD approach primarily intends to incorporate both technical and social aspects equally in the design, implementation, and dissemination of a solution. Since systems which are built upon the wrong assumptions fail (Berg et al. 2003), it is beneficial to involve potential users of new systems early and systematically in the design and implementation for embracing the user perspective (Kushniruk 2008; Drazen et al. 2012). Indeed, the interest in the STSD approach has increased recently, and similar viewpoints exist in related fields, including the design methods such as participatory (Schuler and Namioka 1993), empathic (Leonard and Rayport 1997), or contextual (Beyer and Holtzblatt 1999), which contain STSD concepts. Participatory methods involve users during the design process, which is an important aspect of STSD. On the other hand, emphatic and contextual design approaches highlight the importance of making developers see the users' viewpoints. In addition, the use of agile methods in software development is an area where user participation is especially paid attention to (Abrahamsson et al. 2002). These methods contain at least some face-to-face user involvement and use short iterative cycles to develop evolutionary prototype solutions. In all cases, the importance of incorporating the user perspective is highlighted. In contrast, traditional top–down approaches may obstruct the design and implementation of systems due to limited user involvement.

Regarding healthcare application development, STSD has received increased attention recently (Whetton 2005). A clear understanding of user needs and work structures is fundamental in the development of user acceptable systems, thereby suggesting the STSD approach (Berg 2001; Berg et al. 2003). There are various examples of Health-IT implementations that have failed to be implemented, that have ended up not improving healthcare, and that have been completely abandoned (Chaudhry et al. 2006). Studies in the Health-IT domain demonstrate that understanding the human factor is important while developing a system. Hence, the socio-technical side is an essential part of success in Health IT and correspondingly in mHealth as well (Berg et al. 2003). Accordingly, we incorporate the STSD approach into the design of the representative mHealth solution highlighted in this study. While studies on mHealth adoption and mHealth systems design exist in the literature, these concepts are addressed disjointly, and there is scant research focusing on both aspects. Therefore, this study is an attempt to fill this gap by serving as a unifying approach to these concepts.

In order to reduce the risk of failure, solutions should be developed by considering user needs as well as critical factors highlighted in the mHealth adoption-related literature. Accordingly, incorporation of the user perspective, which is an important focus of the STSD approach, will guide design decisions leading to effective and usable mHealth applications and their proliferation. In this context, a mobile guidance application, named HealthGuide, and its implications for patients and health providers are presented in a representative mHealth application domain. HealthGuide is an mHealth solution primarily addressing the needs of patients who visit healthcare providers for treatment purposes. In fact, the aims of the developed solution are multifaceted: empowering patients and improving the patient experience and satisfaction by providing personalized services in a timely manner while also increasing the quality of healthcare services and the efficiency of the healthcare providers. At its core, HealthGuide utilizes workflows for modeling activities and for assisting patients in performing their activities more efficiently via personalized guidance. This is supported by the use of mobile and pervasive computing technologies in order to collect real-time data for the purpose of helping patients and healthcare providers in managing their activities.

Next, we provide related work in the mHealth guidance application domain. This is followed by the analysis of adoption factors and user needs. The third section describes the HealthGuide system incorporating the user perspective, as suggested by the STSD approach. The capabilities provided by HealthGuide for its potential users are given within the context of an outpatient treatment scenario. Finally, overall benefits and challenges related to HealthGuide are discussed, followed by the conclusion section.

11.2 Related Work

Healthcare processes are complex since they are composed of tasks which may be carried out sequentially or in parallel by a set of participants including patients and clinicians such as doctors and nurses. In order to keep track of such a complex set of activities, workflows are used as powerful models in various application domains. Accordingly, a workflow management system (WMS) may provide guidance to all participants of a health workflow by establishing a structure within a complex setting such as a hospital. The literature regarding WMSs in healthcare includes various studies (Uppu et al. 2006; Mans et al. 2008a, b, 2010; Prinyapol et al. 2009).

In order to provide personalized services in the context of WMS, context-aware computing appears as a promising technology since it offers the ability for mobile applications to discover and react to changes in the environments where users are situated. Accordingly, it may help respond to various contexts of patients to increase the level of satisfaction associated with healthcare services by establishing intelligent context information management. Therefore, it can provide a customized service environment for patients (Lo et al. 2011), and the healthcare domain has been recognized as an important and promising field of context-aware research recently. How to streamline the processes by providing real-time information to healthcare personnel working in hospitals and the achievements provided by utilizing the advantages of handheld devices are defined as important research issues (Hsieh and Lin 2014).

An initial attempt has been made as part of earlier work in order to explore the concept of a workflow-based context-aware mobile guidance framework for managing personal activities, where an application area has been identified as the healthcare domain (Tüysüz et al. 2013). The developed framework and the mobile application are demonstrated to highlight the applicability of the approach in that study. Additional studies exist in the literature with a similar focus, targeting mobile patient guidance systems. The first one is Mobi-Day (Zini and Ricci 2011), which presents a mobile advisory system providing guidance messages for patients. The study addresses issues related to the generation, coordination, and distribution of such notification messages through various devices and for guidance purposes, which include outdoor navigation in particular. Another one is a recently published study by Yoo et al. (2016), where they develop BEST Guide to assist patients not only for outdoor but also for indoor navigation via an indoor location-aware technology using a smartphone combined with WiFi-based indoor positioning technology. It is stated in the study that they aim to use WMS in their future research.

In summary, healthcare has been recognized as a promising application domain for WMS and context-aware pervasive research recently, and patient mobile guidance applications have started appearing. However, there is no such mHealth application using mobile and pervasive technologies in conjunction with a WMS to provide a guidance framework with advanced capabilities, designed by focusing on the user perspective. Accordingly, one of the aims of this study is to fill this gap by extending our previous work on the workflow-based context-aware mobile guidance framework for managing personal activities (Tüysüz et al. 2013) for the healthcare domain. As stated below, HealthGuide has outdoor and indoor navigation modules, similar to other studies mentioned above. In addition, it has more advanced modules incorporating WMS and context-aware pervasive technologies. The user perspective is given next, followed by the HealthGuide system description.

11.3 User Perspective

Incorporation of the user perspective is an important aspect of the STSD approach. To this end, in this study, not only the user needs are identified by collecting information from potential users, but also critical adoption factors are gathered from the mHealth literature as explained below.

11.3.1 User Adoption Factors

Studies state that one of the main challenges associated with mHealth remains as the adoption of related technologies (Riggins and Dewan 2005; Connor et al. 2016). Solutions designed without considering the adoption perspective are prone to fail in practice since they ignore the corresponding critical factors. In order to help to reduce barriers to adoption and facilitate the use of HealthGuide, we have reviewed the mHealth adoption studies. The systematic literature review procedure proposed by Kitchenham (2004) was applied as follows: Technology acceptance theories were selected for the starting point of the search. The search language was English. Search terms of "mHealth," "mobile health" together with "acceptance," "information system acceptance," "adoption," "technology acceptance," "technology adoption," and "patient," "clinician," and "physician" were used. The databases of Scopus and Web of Science were scanned. Over a thousand articles were identified with the search terms. Additionally, their references were reviewed. In the results, journals covered by the SSCI and SCI indexes were included, while other publications (conference proceedings, series, meetings, and reviews) were excluded. A database for managing the search results and the findings was constructed in Microsoft Excel. Publications before the year 2000 were excluded from the database. As part of the first elimination, the studies were evaluated in terms of suitability by examining their keywords, titles, and abstracts, before reading the papers fully. The second elimination was performed by examining the relevance of the study context and the usage of acceptance theories. They were included if the study was related to acceptance or adoption of mHealth and if the study presented information about quantitative results as a result of using acceptance theories. After applying these steps, 28 studies remained, which explore the significant factors. They were considered as a baseline for specifying the most important factors. Card sorting methodology was employed in order to identify the most influential factors to be included in the study. Factor lists were given to five experts with graduate level of knowledge regarding the fields of technology acceptance and behavioral theories. First, they reviewed and sorted the factors independently. Then, they discussed them in a meeting in order to address conflicts and reached a consensus. Accordingly, the most relevant factors were identified and they are briefly described below.

Performance expectancy and effort expectancy are found as significant indicators in the studies based on unified theory of acceptance and use of technology (UTAUT) (Venkatesh et al. 2012), and the corresponding factors defined in technology acceptance model (TAM) (Davis 1989) are perceived usefulness and perceived ease of use, respectively. In addition, other critical factors affecting the adoption of mHealth technologies are identified in the literature as compatibility, perceived service availability, and personal innovativeness. Accordingly, HealthGuide takes these factors into consideration as part of the overall design given in Sect. 11.4.

Performance expectancy (or perceived usefulness) Users' attitudes are explained in relation to their job performance while using technology. It is found as an important indicator in the adoption of mHealth (Wu et al. 2007, 2011; Aggelidis and Chatzoglou 2009; Chen et al. 2010; Lin 2011; Sezgin and Yıldırım 2014; Ducey and Coovert 2016; Kim et al. 2016).

Effort expectancy (or perceived ease of use) Ease of using mHealth applications affects the intention to use them. It is found as another significant factor for adoption of mHealth (Wu et al. 2007, 2011; Aggelidis and Chatzoglou 2009; Chen et al. 2010; Lin 2011; Sezgin and Yıldırım 2014; Ducey and Coovert 2016; Kim et al. 2016). Since workloads are high and people need to access information quickly in the health domain, effort-free applications are needed in hospitals (Gagnon et al. 2016).

Compatibility It is found as crucial for users' performances for the mHealth domain (Wu et al. 2007; Chen et al. 2010; Ducey and Coovert 2016; Okazaki et al. 2016). The technology should be consistent with users' existing values, prior experiences, and needs in order to be adopted. However, the current state of mHealth shows that the technology is still evolving, and incompatible mHealth applications exist (Becker et al. 2014).

Perceived service availability It is found as another significant factor for adoption of mHealth (Aggelidis and Chatzoglou 2009; Wu et al. 2011). Both patients and physicians expect to use mHealth applications for pervasive and timely use.

Personal innovativeness It is found as a critical factor influencing the adoption of mHealth (Chen et al. 2010; Lin 2011; Wu et al. 2011; Okazaki et al. 2016). The users should have a certain level of willingness to use the application (Hung et al. 2012).

11.3.2 User Needs

The essential functionalities of HealthGuide are derived by collecting needs from a set of potential users by utilizing the STSD approach. Conducting interviews with them and incorporating their feedbacks provide the focus on the users.

As a result of the interviews with open-ended questions, which were conducted with five clinicians and eight outpatients, frequently asked questions and the use of information services enabled by pervasive technologies in a real hospital environment are identified. The duration of semi-structured interviews for each person was around 60 min. Visits to a hospital took place on 3 separate days in order to perform the interviews. Some of the open-ended interview questions were:

- What are the frequently asked questions by the patients?
- All things considered, what are the "typical" tasks of the outpatient treatment process?
- What do you think about a mobile application guiding patients? Which functions should it have?
- How much would you be willing to pay for a mobile application to guide you in the hospital?

Then, user needs were identified based on the answers in the interviews as follows: guidance about the next tasks to be followed in a timely manner; navigation to healthcare service locations both outside and inside the hospital; managing appointments through mobile devices; receiving notifications about the time, method, and content of healthcare services such as waiting time, appointment time, explanations about examinations and procedures, and the time of taking prescribed medicines; accessing personal health records in a timely manner; achieving healthcare service improvement; and effort-free user-centered interfaces especially suitable for elderly patients.

11.4 The HealthGuide System

The functional modules of HealthGuide are determined according to the above analysis highlighting the user perspective. The system consists of the following modules: messaging, workflow management, outdoor navigation, indoor navigation, scheduling, and hospital management. Next, the modules and the overall system are described about the user needs and adoption factors.

The messaging module allows the constant exchange of information among the system components as well as other sensors, devices, and information sources in the environment. For example, the system may send a notification to warn the patient. This module satisfies the user need of receiving notifications about the time, method, and content of healthcare services such as waiting time, appointment time, explanations about examinations and procedures, and the time of taking prescribed medicines, as stated in Sect. 11.3.2.

The workflow management module provides a workflow defined by a doctor, a patient, or a workflow designer to be followed through by a patient or clinicians. This workflow may be automatically generated from a set of available templates in a workflow library and customized according to the context information associated with the patient as well as healthcare devices and information sources available in the environment. After the custom workflow is uploaded to the system and enacted, it is presented to the user through the mobile application running on a smartphone. HealthGuide shows the next task to the user, according to the definition in the enacted workflow as managed by the workflow engine. Multimedia files such as image, audio, and video may be uploaded by users for providing supplementary and descriptive information related to the tasks in the workflows. For example, a user can decide to upload a video recording and attach it to a task, with the purpose of giving additional guidance to future users of the same workflow. Accordingly, the system allows the storage of additional information augmenting the task definitions, and this collection is obtained through user submissions. Each task is completed by the manual input of the user or by the system automatically according to the data generated by the sensors and devices in the environment. The process continues as the system presents each task to be completed by the user in order. This module satisfies the user need of guidance about the next tasks to be followed in a timely manner.

The outdoor navigation module provides directions to patients by using GPS data, as they travel to a hospital facility or pharmacies. It expands the patient-guiding service to the outside of the hospital. This module satisfies the user need of navigation to healthcare service locations both outside and inside the hospital.

The indoor navigation module provides guidance to patients within a hospital to help them go from their current locations to indoor destinations on a map, by using real-time location data provided by smartphones combined with WiFi-based indoor posting in the hospital. It uses the location information for context-based accessibility. Similar to the outdoor module, this one satisfies the user need of navigation to healthcare service locations both outside and inside the hospital.

The scheduling module allows patients to access and manage their medical appointments, by automatically providing information about such tasks on a daily basis. Hence, this module helps patients handle uncertainties regarding the care services they receive. Accordingly, it satisfies the user need of managing appointments through mobile devices.

The hospital management module uses data collected via sensors, RFID tags, and the mobile application. Such data may include arrival time of the patient, entrance time of the patient to the doctor's room, appointment time for tests, and test completion time. It also collects patient feedbacks for services via a survey after their completion, for service improvement and customer satisfaction purposes. This module satisfies the user need of achieving healthcare service improvement.

As part of the overall system, timely access to personal health records is provided through the database design of HealthGuide, which addresses the user need of accessing personal health records in a timely manner. In addition, effort-free user-centered interfaces are related to the user interface design of HealthGuide, in order to satisfy the user need of effort-free user-centered interfaces especially suitable for elderly patients. Considering the security aspect of the system, authentication is provided by defined rules, and communications containing sensitive data are handled by encrypted protocols. The relationship of the overall system design with the critical factors identified earlier in Sect. 11.3.1 is discussed next.

Performance expectancy (or perceived usefulness) HealthGuide is aimed to provide practical benefits for both patients and clinicians in their routines, especially while practicing with a tight schedule. Access to information promptly is crucial during their routines (Duhm et al. 2016). Using pervasive technologies in HealthGuide provides access to real-time information, which positively affects performance expectancy. Moreover, an aim of HealthGuide is to improve the performance efficiency of healthcare-related tasks by providing related guidance.

Effort expectancy (or perceived ease of use) We focus on simplicity and providing quick and relevant information in the design of HealthGuide by constructing usable and simple user interfaces, seamlessly integrating the technologies and hiding the complexity in the background.

Compatibility HealthGuide is designed to be customizable so that it becomes compatible and interoperable with hospital management and patient health records management systems, hence affecting compatibility positively. Thus, the meanings of communicated data and information are aimed to be the same when they appear in two different but interfaced systems. This requires the use of communication and architectural standards, medical vocabularies, and appropriate terminology servers. ICD 10 (WHO 2004), which is a coded taxonomy to define health-related problems, is one such open standard. The users can access patient health records through HealthGuide without the need of another system.

Perceived service availability In order to provide service availability, HealthGuide can be deployed on a cloud platform to improve responsiveness and provide effective results by allowing access to the service, independent of time and location. It is stated in Service Level Agreement of Amazon that the monthly uptime percentage is at least 99.95% (Amazon 2012).

Personal innovativeness Underlying reasons regarding the reluctance to use mHealth applications are stated as cost issues, increasing workloads, and unscheduled tasks (Gagnon et al. 2016). In order to reduce the cost of using HealthGuide, it is possible to provide the application free of charge to users, either through subsidies or using sponsors. In addition, one of the aims of HealthGuide is to decrease workloads, thereby increasing users' willingness to use the application.

11.5 HealthGuide and the Outpatient Treatment Process

In addition to the analysis of the user perspective leading to the design of the system, we also present the use of this solution as part of an outpatient treatment scenario, which highlights the capabilities related to the targeted user needs and the mHealth adoption aspect. Similarly, HealthGuide may also prove to be useful in scenarios such as chronic disease treatment, domestic patient care, follow-up postoperative patient, and elderly patient care, since the followed approach is applicable for those application areas as well.

The model of the outpatient treatment process and the interrelation of tasks performed in the process with the HealthGuide modules are shown in Fig. 11.1. We use the standard BPMN 2.0 notation for workflow representation, since it has a wider community of users and can be more easily integrated into information systems based on standard technologies, compared to other workflow notations.

The patient selects the workflow to be followed in HealthGuide (Fig. 11.2a). Following the selection of outpatient treatment workflow, the process starts with the task of signing on to a selected medical service by the patient or patient referral from a doctor. The patient confirms one of the offered appointment date and time alternatives on HealthGuide (via the scheduling module). When the appointment date is approaching, a pop-up reminder message is shown to the patient (via the messaging module). HealthGuide navigates the patient to the hospital facility (via the outdoor navigation module) (Fig. 11.2b) and the related department (via the indoor navigation module) (Fig. 11.2d). When the patient arrives there and completes the payment procedures, the application records the arrival and entrance time data for hospital management purposes (via the hospital management module). At each step throughout the hospital visit, HealthGuide sends notifications to the

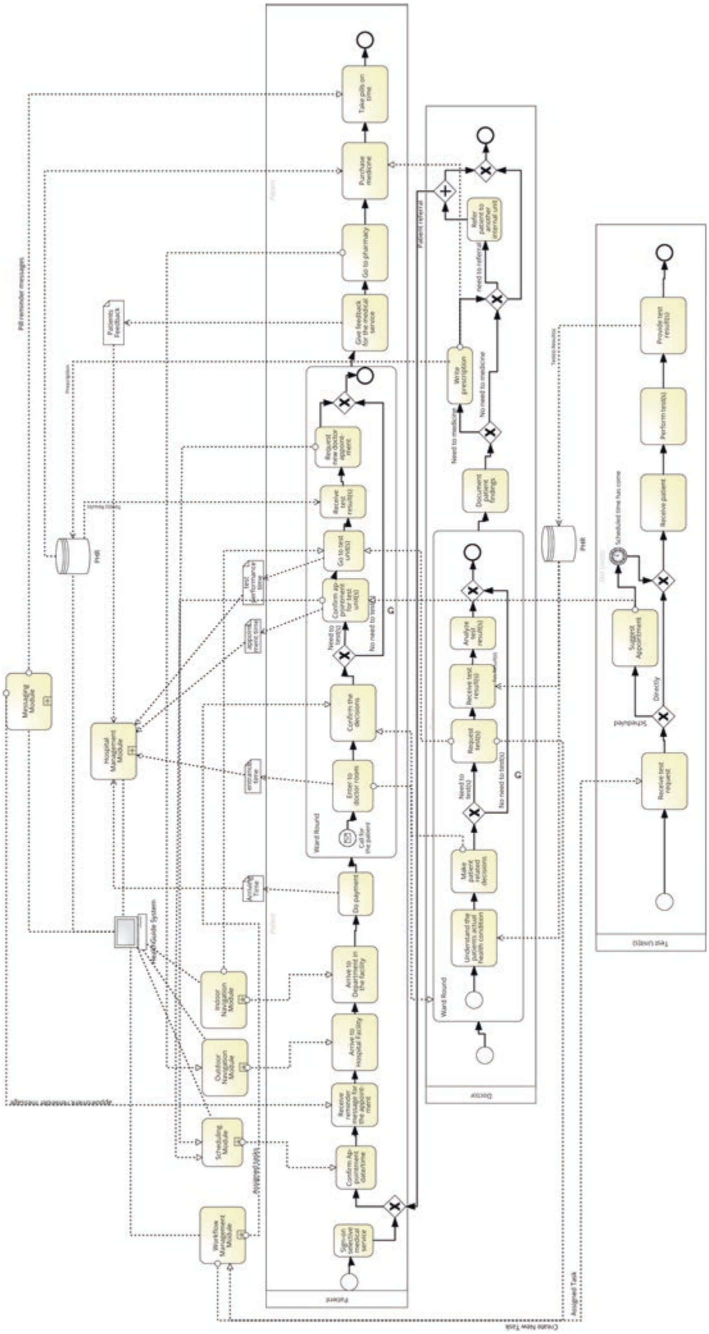

Fig. 11.1 Application of HealthGuide in the outpatient treatment process

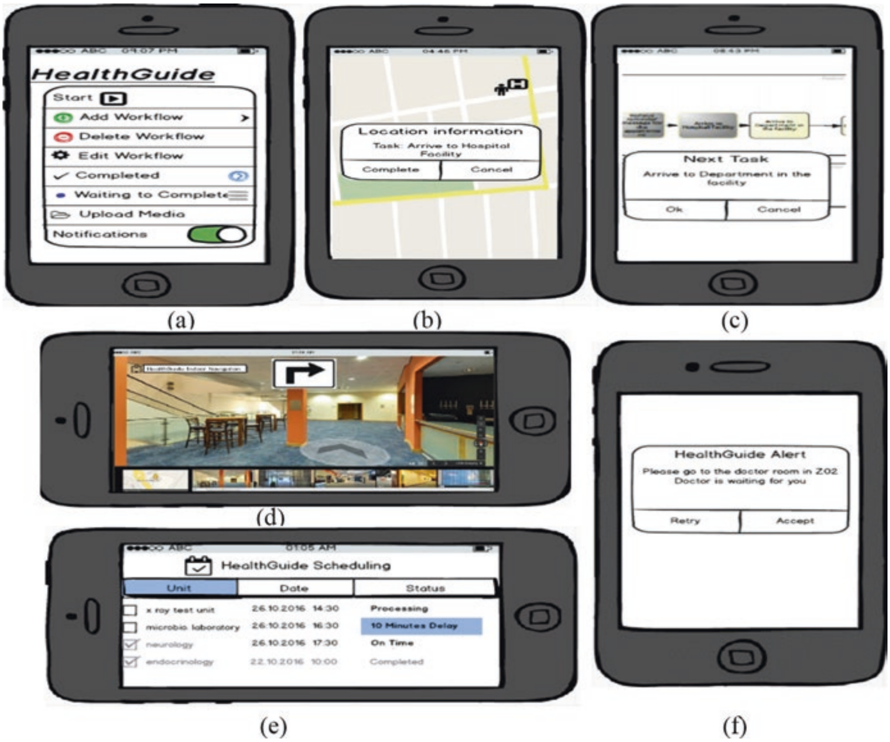

Fig. 11.2 Sample user interfaces of HealthGuide for patients

patient regarding remaining time and possible delay for each task in the workflow (Figs. 11.2c,e, and f). When the patient enters the doctor's room, the first ward round starts, and the rounds are repeated until the process ends. The doctor evaluates the patient's actual health condition by accessing personal health records (PHR) and makes patient-related decisions. If there is a need for tests, the doctor requests them (Fig. 11.3a). As soon as this request occurs, both the patient and the personnel working in the test unit access the assigned tasks on their mobile devices (via the workflow management module). If the test unit performs work according to scheduled appointments, the available appointment times are offered to the patient via a pop-up message upon receiving the test request, and the patient confirms the appointment time for the tests. The workflow followed by the patient is updated based on the appointments for the test requests created by the doctor. A pop-up reminder message is shown to the patient when the scheduled appointment is approaching (via the messaging module). HealthGuide guides the patient to the test unit (via the outdoor and indoor navigation modules) (Figs. 11.2b and d). The test unit performs the requested tests. The test results stored in PHR database are accessible by the doctor and the patient. When the test results are available, both the patient and the doctor are notified by pop-up messages (via the messaging module). Next, the patient requests a new appointment with the doctor for consultation

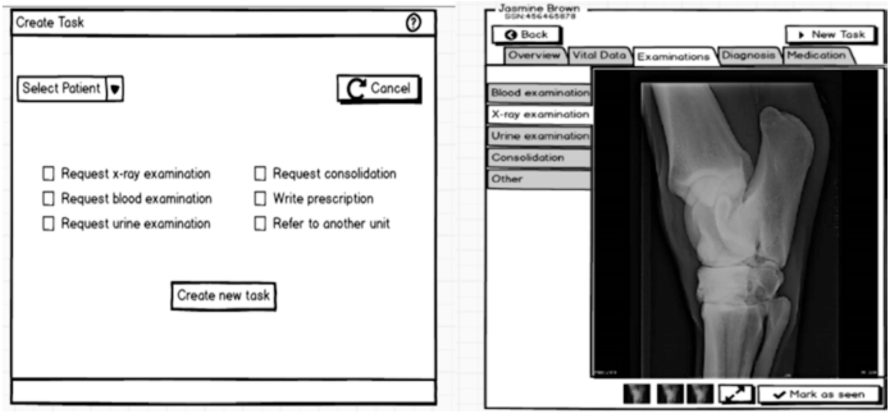

Fig. 11.3 Sample user interfaces of HealthGuide for doctors

regarding the test results (via the scheduling module). Since the new appointment time may not be immediately available, a notification message is scheduled to warn the patient about the appointment later on (via the messaging module). When the patient goes to the doctor's room, the doctor analyzes the test results (Fig. 11.3b), documents the findings, writes a prescription if needed, and refers the patient to another unit or internal service, if needed. After the completion of the tasks, the patient is requested to fill a survey to be used for hospital management purposes (via the hospital management module). HealthGuide guides the patient to the nearest pharmacy (via the outdoor navigation module) (Fig. 11.2b).

The patient gets the prescriptions by utilizing the barcode scanner of HealthGuide, which also reminds taking the medicines when the time comes. The message also includes information regarding the type, dose, and usage instructions of the medicines (via the messaging module).

11.6 Benefits and Challenges

HealthGuide, which is developed based on the socio-technical system design (STSD) approach, aims to provide guidance services to patients by utilizing pervasive technologies. Benefits and challenges associated with HealthGuide are discussed by highlighting both the social and technical issues in this section.

11.6.1 Benefits of HealthGuide

Improving patient performance If a process is modeled as a workflow describing tasks and their sequences, the user can track the tasks step-by-step. The provided pervasive WMS automatically or manually keeps track of the completion of tasks and notifies the user for the next task until the assigned process is completed. Thus, the user is not confused about the order of the assignments, does not perform unnecessary tasks, and, most importantly, does not skip a required step. Overall, the decreased time for completing all tasks results in improved patient performance.

Improving patient experience and satisfaction Patients frequently need to move from place to place and follow directions to complete all tasks. They may be elderly, sick, physically, or psychologically weak and concentrated on their diseases almost exclusively. HealthGuide eliminates unnecessarily performed tasks as well as time wasted while searching for the right place. In addition, patients avoid misinformation and get informed about possible delays regarding their appointments. For instance, by using HealthGuide, it is not necessary for patients to find and ask someone if it is their turn or not. They can also leave the waiting room without the fear of missing any announcements.

Providing personalized services Healthcare processes show variability depending on the unique circumstances of each patient and the directions given by their doctors. Accordingly, every task will be uniquely instantiated with its specific context. Knowing and using the current context of the patient enables linking health activities with the pervasive computing environment for utilizing relevant information (Pryss et al. 2010). Therefore, HealthGuide can provide context-aware and personalized guidance to patients through the use of pervasive technologies.

Increasing patient involvement HealthGuide is empowered with the crowdsourcing approach, where users and workflow designers can augment tasks by attaching related descriptive text, audio, image, and video content. This is used to help other users of the same workflow to carry out their activities more easily.

Safety and reduction of errors Through the use of HealthGuide, accessing accurate data about patients such as their identity information and medical histories helps prevent errors regarding clinical procedures. This is of utmost importance from the perspectives of all stakeholders including patients, doctors, and hospitals.

Improving service quality by utilizing accurate data The utilization of accurate data improves reliability and consistency related to the quality of healthcare, which is referred to as essential issues in the mHealth domain (Barton 2012). As stated by Aitken and Lyle (2015), hospitals lack real-time information that is integrated into their workflows and that is used to aid clinical decision-making. The development of mechanisms for this purpose is challenging due to the dynamic nature of activities in hospitals. The use of pervasive technologies to collect accurate data in the hospital environments enables HealthGuide to provide a solution. Accordingly, the integration of relevant data into personalized workflows supplies timely and accurate information to patients, which in turns improves the quality of health services.

Improving collaboration among clinicians Healthcare providers are searching for ways to increase the quality of treatments by improving the collaboration among clinicians. Accordingly, clinicians can use mHealth tools to share data and communicate more efficiently. For instance, they can access an assigned task such as an x-ray test request as soon as the doctor requests it. Similarly, the doctor is notified when the requested test results are available in HealthGuide. This in turn increases clinicians' collaboration.

Increasing clinicians' efficiency The effective allocation of available limited resources helps facilitate the delivery of a large variety of medical services. Related to this, clinicians' efficiency is increased as a result of accessing accurate medical information anytime, anywhere as the information is provided at the point of need. Therefore, HealthGuide is also beneficial for clinicians, since it relieves them from the burden of calling and accompanying patients all the time. With this, clinicians can allocate time for a larger number of patients and provide them better services. It also results in reduced waiting and consultation time.

Decreased costs HealthGuide helps decrease costs for both the patient and the healthcare provider sides. Such a decrease is associated with the increase in system efficiency and improvements in provided services. The workloads of both the clinicians and help desk personnel are decreased since they do not waste time guiding patients. In addition, timely and accurate treatment can lead to a decrease in unnecessary hospital visits, which in turn causes improvements in both patient and hospital clinician efficiencies.

Interoperability Interoperability is a critical issue in the mHealth domain. The system should be capable of integration regarding data exchange through the use of taxonomies such as ICD-10 (WHO 2004). Accordingly, HealthGuide can be customized using additional interfaces. Patients may have multiple clinical needs and conditions and may interact with health systems via multiple endpoints. HealthGuide can provide interoperability and accurate exchange of information with other systems such as hospital management systems (HMS). With this, the updated information is immediately accessible by other participants.

Process improvement Collected context-aware data such as the arrival times of patients, their entrance times to the doctors' offices, appointment times for tests, test completion times, and patient feedbacks are made available for process mining to detect problems and improve processes (Van der Aalst 2011). In turn, this provides delivery of high-quality care while also reducing costs.

Collecting data from patients about health services The user is requested to fill a survey after completing a workflow in HealthGuide. This feature helps the hospital management by providing clinical surveys containing comprehensive information on patients' conditions.

11.6.2 *Challenges of HealthGuide*

11.6.2.1 Social Challenges

Barriers to adoption There are various social factors at play regarding the use of HealthGuide, such as age and medical condition of patients as well as the point of views of clinicians and associated mobile anxiety. Older adults and patients with difficulties may not be comfortable with using mobile devices to access HealthGuide services. Additionally, clinicians may resist adopting the application due to their significant workloads and fear of losing their jobs. Training patients and clinicians can offer a solution toward reducing barriers to adoption of mHealth. However, the HealthGuide system may still not be suitable for handling emergencies, which have special circumstances.

Patient confidentiality In HealthGuide, users and workflow designers can upload supplementary text, audio, image, and video content to inform other users regarding workflow tasks. However, special care must be applied. As stated by Visvanathan et al. (2011), taking photos of patients with mobile devices raises the issues of consent, safe storage, and patient confidentiality.

Government policies and regulations Policies and regulations should promote alignment with strategic health goals, common ICT standards, and partnerships for collaborating nationally and internationally. However, laws and regulations related to mHealth applications are at early stages (Barton 2012; Becker et al. 2014), and there is a need for government policies and regulations. For instance, sharing of confidential information with third parties should be regulated by laws.

Ethical issues The data collected by mHealth systems are sensitive due to the privacy issues associated with individuals. Hence, such data must be handled carefully. For instance, processing data derived from HealthGuide for data mining purposes or sharing of such information may cause ethical issues regarding race, gender, and sexual orientations of patients.

Varying organizational conditions and cultures between hospitals While there may be commonalities among organizations, workflows in HealthGuide should be customized for each hospital. Similarly, the maps and other content will be different in each case.

The risk of misinformation Content uploaded by users may lead to misinformation. A centralized or crowdsourced control mechanism should be constructed to check the appropriateness of uploaded information by other users.

Multidisciplinary interaction Since the pervasive WMS for health is an interdisciplinary solution, there is a need for management of interaction and collaboration among many actors (patients, clinicians, hospital managers, governments) to avoid unnecessary redesigns and overspending.

11.6.2.2 Technical Challenges

Data privacy and security Data privacy and security in the healthcare landscape are never ending challenges (Hale et al. 2015; Kumar et al. 2013). PHR can be a target of cyberattacks due to its significance. A flaw in any part of HealthGuide can expose the PHR. Although there are authentication rules defined in HealthGuide to prevent unauthorized access and to fulfill legal obligations, keeping PHR safe is a complicated mandate.

The lack of common data standards mHealth applications need reliability and consistency to maintain healthcare quality (Barton 2012), and the lack of standardization and regulatory frameworks is a major challenge regarding the implementation of mobile applications (Barton 2012; Becker et al.. 2014). This causes interoperability issues including seamless communication with existing information systems.

Data protection and disaster recovery A business continuity plan is also essential where there is provision for data protection and disaster recovery. Since HealthGuide can be deployed on the cloud, the control is on the cloud provider. In addition, regulations for protecting electronic data are also required.

Big data management on the cloud Large amounts of data are collected and analyzed in real time to provide useful services to patients in HealthGuide. This poses problems regarding bandwidth and storage. While a possible solution is to embrace the cloud paradigm, it has many implications such as privacy, security, multi-tenancy, and access control-related issues, due to its scale. In addition, statistics and artificial intelligence communities face significant challenges in handling such large-scale data for analysis and mining purposes.

11.7 Conclusion

Considering the possible benefits offered by mHealth applications, it is important to embrace a socio-technical perspective while designing such systems to facilitate their adoption by users. In this chapter, we present such an mHealth solution in the form of a personalized mobile patient guidance system, named HealthGuide, utilizing pervasive technologies in conjunction with a WMS that is used to model complex workflows in a hospital environment. The design and development of HealthGuide are carried out by starting with identifying the needs of its possible users. In addition, critical factors associated with adoption of mHealth application have been gathered from the literature to obtain additional guidance regarding the system design decisions toward the end goal of facilitating user adoption of such a new mHealth offering. Accordingly, the user perspective is incorporated as part of the socio-technical system design (STSD) approach.

HealthGuide offers guidance services to patients by hiding the complexities associated with workflows in hospital visits. This capability is enhanced with pervasive technologies used to collect data related to tasks in the workflow. The system also provides capabilities to deliver timely and relevant information about tasks in the workflow. An implementation of HealthGuide in the outpatient treatment process is demonstrated as a sample scenario to present its capabilities with respect to user perspectives. In addition, the benefits and challenges associated with the solution are discussed by highlighting both the social and technical issues.

As future work, a cost-benefit analysis of the system would be helpful to offer insights regarding investments needed. Application of an iterative, incremental change process may be applied, and at every new step, the lessons learned from the previous steps should be properly integrated and acted upon. The implementation of HealthGuide in other healthcare scenarios may be carried out. The deployment of the system in a hospital setting may help collect real data for quantitative analyses, which may also be used for advanced usability studies regarding such an mHealth solution.

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Chapter 12
Mobile Applications User Trend Analysis of Turkish Physicians in Digital Environments

Elgiz Yilmaz Altuntaş

12.1 Introduction

Digital media in general and smartphones and mobile applications in particular have revolutionized the way human beings interact with each other. Despite the impact of mobile technologies on health communication and physician-patient relationships, medical communities have remained limited in the use of these technologies in their clinical practices.

Smartphones were launched 16 years ago and made computer functions available in mobile phones. While the number of smartphone users in Turkey increased by 96.9%, the percentage of tablet users was 29.6% in 2016 (Turkish Statistical Institute 2016). By 2018, each mobile device user will have used three gigabytes of data on average (Deloitte 2016).

Considering the statistics around the world, Turkey has shown a rapid improvement in Internet and social media utilization. According to the data provided by the Turkish Statistical Institute (2016), the rate of Internet utilization for the age group of 16–74 was 55.9% as of April 2015. The percentage of household members who have access to the Internet was 69.5%, while the percentage of households with mobile phones or smartphones was 96.8%. According to International Telecommunications Union (ITU), in Turkey, the number of Internet users in Turkey was approximately 2 million by the early 2000s, while the number has increased by 1750% in the last 10 years (International Live Stats 2016). According to the data provided by "WeAreSocial," a website that compiles the data from Global Web Index, the number of active Internet users in Turkey as of June 2015 was 37.7 million (49% of the population), the number of active social media accounts was 40 million

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E. Sezgin et al. (eds.), *Current and Emerging mHealth Technologies*,
https://doi.org/10.1007/978-3-319-73135-3_12

Table 12.1 Popular social platforms in Turkey and utilization rates in 2015

Social platforms	Utilization rate (%)
Facebook[a]	26
WhatsApp[b]	23
Facebook Messenger[b]	21
Twitter[a]	17
Google+[a]	14
Skype[a]	13
Instagram[a]	12
LinkedIn[a]	8
Pinterest[a]	7
Viber[a]	8

[a]Social platforms
[b]Instant messaging platforms

(52% of the population), and the number of active mobile social media accounts was 32 million (42% of population) (Wearesocial 2016). According to the data from 2015, the increase in the number of Internet users was 5%, the increase in social media accounts was 11%, and the increase in mobile social accounts was 14%. The same data shows that the average time spent on Internet by Turkish users is 4 h and 37 min, while the average for mobile Internet usage is 2 h and 51 min, and the average time spent on social media by Turkish users is 2 h and 56 min.

Based on the data from WeAreSocial (Wearesocial 2016) for June 2015, the social media platforms preferred by Turkish users and the utilization percentages of these platforms are listed in order of popularity (Table 12.1).

Mobile devices are increasingly more integrated with communicational and clinical tools. In order to determine the best ways these new technologies can be used in practice, it is extremely important to monitor utilization characteristics and prevalence of these platforms among physicians. A nationwide survey in 2011 conducted with the participation of 3306 respondents revealed that more than half of the participants used various applications in the clinical practices, including textbook references, classifications, and treatment algorithms (Franko and Tirrell 2012).

12.2 Mobile Apps and Patient-Centered Communication

In the Wolters Kluwer Health 2013 Physician Outlook Survey (2013), which explores the most common issues and challenges physicians need to overcome as part of their practices from patient care to profitability, more than half of the physicians are in agreement on the progress made through the improvements in healthcare information technologies, which ensure patient safety and improve patient care. Of the physicians, 39% also remark the progress in improving patient relationships, and 34% remark the progress on increasing efficiency/time saving.

The survey also reveals that more than half of the physicians (55%) use both smartphones and tablets in their daily practices, 33% use smartphones, and 17% use tablets to directly contact their patients (The Wolters Kluwer Health 2013 Physician Outlook Survey 2013). The most common purpose the smartphones are used for is reaching drug information, while tablets are mostly used to access medical studies. In addition, 24% of the physicians use mobile applications, and they indicate that mobile health applications are the most popular digital/social media platforms used among them for professional purposes (The Wolters Kluwer Health Physician Outlook Survey 2013).

Smartphones have come into prominence as essential devices serving as a reference that provides assistance for patient care, monitoring, rehabilitation, communication, diagnosing, teaching, and researching. Due to the concerns regarding patient safety, changes in patient behavior, quality of care, confidentiality of data, and threats from cyber attacks, it is suggested that the applications must be developed in concordance with a governance framework (Charani et al. 2014; Wu et al. 2011). The applications can be downloaded for free through online application stores and are available for all commonly used mobile platforms such as Android, iPhones, and Windows mobile.

Among innumerable communicational applications, WhatsApp[1] has become one of the most popular applications partly because of its cost/effectiveness. WhatsApp, a cross-platform mobile instant messaging application, allows for the exchange of messages and media over the Internet. The number of WhatsApp users, which was 500 million in 2014, reached more than 1 billion in February 2016 (Deutsche Welle 2016) in over 180 countries who use WhatsApp to stay in touch with friends and family, anytime and anywhere. WhatsApp is free and offers simple, secure, and reliable messaging and calling, available on phones all over the world McMillan (2014). A popular feature, the group chat, allows people to communicate and share images and videos over a common interface with up to 50 members in a group. Through the application, it becomes possible for physicians to establish the necessary intradepartmental communication about patient admissions, procedures, postoperative instructions, transfers, discharges, and reviews. It also helps healthcare professionals to communicate frequently about patient imaging findings, laboratory reports, and wound status updates.

Another instant messaging service, Facebook Messenger, was developed by Facebook, which is one of the most popular social platforms in the World. Instant messaging on Facebook is possible through logging in to the Facebook account and gaining access to send messages to favorite contacts. It allows users to send pictures, attachments, and GIF files to the friends in their contacts and start video conversations with them through either Facebook chat or Messenger.com. Moreover, the group messages feature on Messenger makes messaging between more than two users possible. The group messaging feature allows users to chat with multiple friends in a group conversation and send videos and pictures to them.

[1] www.whatsapp.com/about.

Facebook has recently announced its new feature, "Messenger for Business." It is expected to be the most effective feature of the website seen until today. This application makes it possible to add a Facebook Messenger box to websites, and therefore, visitors are able to send a message to the website directly without having to open a new Facebook tab. As the messages sent can be displayed in the Facebook Messenger conversations, the messaging traffic is accelerated. The social media integration of "Messenger for Business" makes a distinguishable impact on the health sector (Dijital Ajanslar 2017). Because hospitals, healthcare practices, and medical facilities are increasingly using instant messaging to improve internal communications and provide the best patient care available. Facebook Messenger system that allows for file sharing enables staff to share information like X-rays, prescription, treatment schedules, follow-up appointments, and more.

In addition to this, the phrase "patient-centered healthcare" gets thrown around a lot in the healthcare. As consumers, patients are realizing the power of choice and being more selective about who provides them with the care they need. This means that quality improvement and patient relationships are more important than ever. Having a CRM system that can keep track of who your patients are, what medications they're on, who else provides them with care, and other important pieces of information can help you get a picture of who your patients are overall. Analyzing these things that improve the quality of healthcare, such as building patient relationships, can actually increase patient satisfaction, which in turn can improve other important metrics. Since the Messenger for Business expedites contacting doctors and hospitals through their web pages and paves the way for the healthcare providers to be able to devote close attention to the expectations of their patients, this function is a revolutionary one. Onward from the date the function hit the stores, a considerably increased intensity in the messaging traffic was observed. The opportunities for visitors to receive a reply in a short span of time and to contact experts without losing time also help to preserve the trust of users.

The advancements in the computing power of smartphones and the popularity of mobile applications lead mobile devices to play a significant role in the patient-oriented healthcare, which gains more importance with each passing day. The "medicalized smartphone" does not only provide web-based access to health resources for patients but also can run patient-oriented software applications and is connected to health-related peripheral devices. Physicians used to send text messages and e-mails to distribute perioperative updates via mobile devices to patients' relatives, but the instant and secure way of transferring patient data is considered very important by physicians, patients, patients' families, and caregivers (Gordon et al. 2015). Although mHealth applications offer many potential benefits, the applications also spark reactions since they require the private medical information of users in order to function properly (Dehling et al. 2015). To develop a completely secure and reliable healthcare application, the issues of security and privacy as well as other aspects must be considered in the design, development, and implementation stages of the applications.

12.3 Mobile Usage Adoption and Challenges for Physicians

The General Medical Council (GMC)[2], which was established in England in 1858 with the purpose of protecting, improving, and rendering sustainable community health by assuring the relevant standards for medical applications, published a draft on the 18th of April, 2012, which is entitled "Good Medical Practice: Explanatory Guidance." The GMC plays a significant role in the publication of guidebooks on the necessity of continuous professional development and the roles of relevant organizations and in the re-approval of physicians. The openness of the draft on the utilization of social media by physicians for interpretation and comment was accepted in 2013 after being published in *The Lancet* website, a globally reputable medical journal, on the 28th of April, 2012 (Good Medical Practice 2013). There are two issues emphasized on the utilization of new technologies by physicians: honesty and respect. These issues are essential for not only communication with colleagues but also all ways of communication and interaction. An attention should be paid to the truth and provability of information given when communicating with the society (including advertising activities, texts, and speeches), the protection of patient information confidentiality, and making sure that the patients' lack of medical knowledge are not exploited.

Physicians must be honest and trustworthy in all ways of communication with colleagues and patients. They must present all the demanded information, which are considered as accurate. Physicians must act by obeying the limits of the information they possess and must not provide false or misleading information. They must not share any information that may cause recognition and exposition of the patient in a public environment.

The utilization of social media has removed the border between public and private life and has made the accessibility of personal information possible. When using social media, physicians must act by knowing the online privacy limits regarding the issues of privacy and access to information. Despite all privacy settings, they can never be sure that their profile and information are not accessed by other sites since this cannot guaranteed by any social media websites. It is possible that physicians' information may be available for employers, future employers, and patients who have access to their accounts. Once the physicians' information is revealed, it must be taken into account that this information may be shared by others, may be commented on, and may become almost impossible to be removed. Moreover, the physician-patient relation is based on trust, so privacy is a necessary aspect of this relation. When using the social media, receiving patients' approval and obeying the privacy-related rules are essential. All information shared on the social media may not be per se sufficient for the exposition of patient identity. However, GPS coordinates, the information stated on images, and tags may cause patient identity to be exposed.

[2] http://www.gmc-uk.org/about/index.asp.

Using social media is potentially beneficial for physicians in establishing communication with their colleagues and patients. It contributes to the success of treatments and improves professional relations. Social media also contains risks unless the limits of private and professional life are clearly delineated by the users. Physicians must take into account professional limits when communicating with patients in any way. If the patient reaches a physician through his/her private profile, the physician must express that the patient's access to the private profile can be inappropriate and then must redirect him/her to the professional profile (e.g., website, LinkedIn profile, telephone).

Physicians must not use social media specifically to discuss about a patient or their treatment. When they interact with people and organizations or make a comment in the online environment, it must be in mind that just as written and verbal communication, this situation also is subject to copyright, and related regulations should be complied.

The Food and Drug Administration recently published a guideline on "Mobile Medical Applications: Guidance for Food and Drug Administration Staff" (FDA 2015). The FDA encourages the development of mobile medical apps that improve healthcare and provide consumers and healthcare professionals with valuable health information. The FDA also has a public health responsibility to oversee the safety and effectiveness of medical devices – including mobile medical apps. Regarding to FDA, some of these new mobile apps are specifically targeted to assisting individuals in their own health and wellness management. Other mobile apps are targeted to healthcare providers as tools to improve and facilitate the delivery of patient care. It has been stated regulatory approaches for usage of these mobile medical apps. Thus, this study aims to collect significant and beneficial findings to understand physicians' perception of mobile apps and their intentions to use these apps in medical and daily communication practices with their patients in Turkey.

Although mobile device technology has revolutionized interpersonal communication, the implementation of this technology in the physician-patient relationship still remains limited due to concerns over patient confidentiality and the security of digital information. Nevertheless, the efforts for improving communication between physicians and patients in all fields of medicine as a way of improving patient care still continue.

12.4 Methodology

12.4.1 Overview

Within the scope of this study, the preliminary findings from an online health communication survey titled "Mobile Apps User Trend Analysis of Turkish Physicians" are reported. The survey aims to understand physicians' perception of mobile apps and their intentions to use these apps in medical and daily communication practices with their patients. This study also focuses on discovering the behavior of physicians and the applications they download related to healthcare, medical information, and their patients' health history.

The study was performed with the participation of 2786 physicians from internal medicine departments in Turkey through TCMSFA (www.tcmsfa.com), which is a product developed specially for the needs of *field sales forces* in healthcare and pharmaceutical industries, that enables to gather data such as visited physicians, unit, hospital, date, time, how many times, which details, feedback to e-detailing, and CRM. In the study, 2786 physicians were selected from 7000 physicians from internal medicine departments in Turkey. The sample was based on an accessible and convenient sampling from a clustered data in state, private, and university hospitals in Turkey. Quantitative analyses were conducted. The frequencies were given for categorical variables such as demographic distribution of physicians by their medical specialty and the physicians' mobile application user behavior by hospital type.

The survey was designed to investigate the utilization of mobile applications by doctors of internal medicine and endocrinologists in the clinical setting. The participants answered the questions during planned field visits by medical representatives between December 2016 and January 2017. Upon the evaluations that took over a period of 1 month, it was seen that mobile applications have become widely used tools in the clinical settings and are adopted by physicians.

12.4.2 Physician Confidentiality and Mobile Platform

To ensure the privacy of the physicians who participated into the study, all soft copies of data were stored in locked files with restricted accessibility. Each of the physicians was assigned to a code number in order to keep participants' identity confidential. The data sheets containing participant identifiers and subject identification numbers were stored separately from the other data sheets.

Data collection process was carried out in accordance with standard protocols. Based on the information acquired from TCMSFA (www.tcmsfa.com), a product that enables to gather data such as visited physicians, unit, hospital, date, time, how many times, which details, feedback to e-detailing, CRM, and doctors of internal medicine and relevant departments, two questions were framed for each physician. While one question pertains to the utilization of mobile application in communication with the patient, the other is related to the utilization of mobile health application in continuous self-improvement.

12.5 Principal Findings

In total, 2786 physicians from different areas of expertise in private and public health organizations of Turkey have participated in this study. In order to provide a representation of Turkey, they were from different areas of expertise in health organizations at all levels in almost every city of Turkey. The questions were asked to them face to face with the help of medical representatives of Bilim İlaç, the agency of TCMSFA mobile product "Mobilim."

The demographics of physicians were as follows: internal diseases specialists ($n = 2547$), endocrinologists ($n = 209$), family physicians ($n = 22$), nephrologists ($n = 3$), cardiologists ($n = 2$), internal diseases dialysis experts ($n = 2$), and pediatrician ($n = 1$).

These physicians provide services at training and research hospitals ($n = 638$), state hospitals ($n = 1036$), city hospitals ($n = 9$), university hospitals ($n = 505$), private hospitals ($n = 477$), medical centers ($n = 120$), diabetes center ($n = 1$), dialysis center ($n = 1$), and imaging centers ($n = 1$). They are affiliated with the Turkish Ministry of Health.

Of the 2786 physicians, 2138 (76%) stated that they do not use mobile applications in order to communicate with their patients, while 362 of them (13%) stated that they prefer platforms like WhatsApp, Facebook Messenger, or SMS texts to communicate with their patients. Of the physicians, 286 (11%) stated that they use applications such as UpToDate, Epocrates, Calculate, and DynaMed for professional development within the scope of continuous medical education. The tendencies of physicians were also examined in terms of the use of mobile applications by the type of the organizations they serve at (Table 12.2).

The results show that 776 of 1036 (75%) physicians serving at state hospitals stated that they do not use mobile applications to communicate with their patients during the treatment process whereas 167 (16%) stated that they use mobile applications for communicating with their patients, and 94 of them (9%) stated that they use mobile applications developed by overseas companies for their personal professional development.

While 518 of 638 physicians (81%) serving at training and research hospitals stated that they do not use mobile applications to communicate with their patients during the treatment process, 65 of them (10%) stated that they use mobile applications when communicating with their patients, and 55 (8%) stated that they use mobile applications developed by overseas companies for their personal professional development.

Table 12.2 Physicians' mobile application user behavior by hospital type

	Behavior type		
Hospital type	Don't use mobile app to communicate with patients (%)	Use mobile app to communicate with patients (%)	Use mobile app for their personal vocational development (%)
State	75	16	9
Training and research	81	10	8
University	73	10	18
Private	98	17	10

While 367 of 505 physicians (73%) serving at university hospitals stated that they do not use mobile applications to communicate with their patients during the treatment process, 48 of them (10%) stated that they use mobile applications when communicating with their patients, and 90 (18%) stated that they use mobile applications developed by overseas companies for their personal professional development.

While almost all of the 477 physicians (98%) serving at private hospitals stated that they do not use mobile applications to communicate with their patients during the treatment process, only 81 of them (17%) stated that they use mobile applications when communicating with their patients, and 46 (10%) stated that they use mobile applications developed by overseas companies for their personal professional development.

12.6 Discussion

The introduction of the applications which allow for sharing information among closed groups has paved the way for secure communication among healthcare professionals. They have a potential for taking patient care to the next level. Following health communication literature underlying patient engagement through mobile technologies in physician-patient relationship, we decided to analyze if there was any change in the traditional practice as a result of the introduction of smartphone applications and their widespread utilization, cost and time effective, and availability. Our research revealed that WhatsApp and Facebook Messenger are the most commonly used communication tools among the physicians in Turkey. However, according to the results of our research, the physicians prefer to use mobile applications much more for their personal and professional development than for the communication with their patients. The findings suggest an important need to examine in detail these web-based learning technologies, environments, and systems which are defined as portable, flexible, accessible to multimedia, and being able to look up information quickly. This is particularly important as the Internet grows in popularity as a medium for knowledge transfer. In this context, improvements in health communication have the potential to play a significant role in the development of a promising new tool for patients/consumers and healthcare providers.

The previous studies showed that the utilization of smartphones has improved the communication among healthcare professionals (Wu et al. 2011). Our findings are similar to ones acquired from these studies. A high level of awareness was also observed among physicians as a result of their adoption of WhatsApp and Facebook Messenger that allowed patient-related information exchange and that of UpToDate, Epocrates, Calculate, and Dynamed mobile applications that allowed continuous self-medical education. In their study on the utilization of smartphones in medicine, Lo et al. (2012) concluded that the utilization of mobile devices with e-mail function helps physicians to prioritize calls and respond in the appropriate way, easily contact with their colleagues at different locations in the hospital, efficiently communicate with their patients as well as with other professionals.

12.7 Conclusion

There is a growing body of reasons that promote the utilization of mobile applications in medical interventions. These reasons include the utilization of applications for smoking cessation, other behavior changing programs such as exercising and weight management, and self-management on long-term conditions such as diabetes. However, there is relatively narrow-scoped research on the feasibility or effectiveness of downloadable applications or software for mobile phones for effective communication with patients. We expect these trends to continue and encourage providers and trainees to be aware of the limitations and risks inherent in new technologies.

Our results indicate that the introduction of the smartphone application "WhatsApp" can lead to improvements in patient-oriented awareness and communication. However, it is important to emphasize that the practice of using WhatsApp is not a substitute for clinical examination, but it can play a supportive role in enhancing the level of patient care.

The physicians mostly accept that the Internet allows healthcare to be continuous by allowing patients to be active participants in their own care. Our survey also found that the physicians think text messages and Facebook Messenger are as helpful as in-person or phone conversations with their patients especially in primary care. Some of our participants mentioned that: "if you want to give a patient an update or if they need to come in for a lab test or for test results; it is a great tool. It would not be breaching confidentiality." But they highly recommend separating public and private identities on social networks, especially on Facebook because of the need to preserve privacy between physician-patient relationship.

Such systems can greatly improve the level of communication between physicians, patients, and patients' families and caregivers. All types of users declare a high level of satisfaction with these systems. Based on these findings, it is concluded that the functions offered by the ongoing advancements in the smartphone technology, healthcare applications, and device development should be expanded in order to enhance patient-oriented care in the future.

Acknowledgments Assistance provided by Cem Tozar (Business Unit Manager – Bilim Pharmaceuticals), Onur Kurtuluş Dilber (Promotion Manager – Bilim Pharmaceuticals) with their physician network, and M.Özgür Altuntaş (Managing Partner – TCM) with their field sales force automation product "TCMSFA" has been a great help in collecting and gathering data.

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Chapter 13
Acceptance of Mobile Homecare Technologies: An Empirical Investigation on Patients with Chronic Diseases

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13.1 Introduction

World Health Organization (WHO) (2011) identified chronic disease as "the disease of long duration and generally slow progression." Chronic diseases are leading to cause mortality in the world by representing 60% of all deaths. According to WHO, out of the 35 million people who died from chronic disease in 2005, half were under 70, and half were women (WHO 2011). According to the "Chronic Diseases Report" of Ministry of Health's General Directorate of Curative Services (2006), there are about 22 million people who live under the influence of chronic diseases in Turkey, and the number of patients with chronic disease is increasing. In the report, the most important risk factors for the group of chronic diseases, namely, cardiovascular diseases, high blood pressure, diabetes, and COPD, were emphasized as smoking and alcohol use, unhealthy diet, stress, and sedentary lifestyle. In addition, the report stated that protective measures can be taken for chronic diseases, which otherwise led to early death and adversely affecting the quality of life. Chronic disease is an ongoing long-term condition. The complications of this condition are costly to the health system and cause losses in productivity. Due to the increase in both the prevalence of the patients with chronic diseases and the elderly population, the cost of the complications is about to reach to dramatic levels. Thus, the measures should be taken to be able to prevent their adverse progression and to keep complications minimum (Kyriacou et al. 2003). To achieve this goal, healthcare services have been shifting from treatment to prevention (Lin et al. 2008). By the progress in medical

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E. Sezgin et al. (eds.), *Current and Emerging mHealth Technologies*,
https://doi.org/10.1007/978-3-319-73135-3_13

sciences and information technologies (IT), it has been possible to manage chronic diseases within the living area via homecare technologies.

The chronic diseases need continuous monitoring, such as tracking diagnosis results, keeping medical images, collecting of vital signs, for better management of the diseases. However, such routine management cannot be performed all the time by the healthcare providers at a healthcare centers. Thus, chronic disease management has to be carried by the patients. As an example, a diabetic patient has to perform several tests per day to adjust the blood glucose level with medication. This is the only way to identify if the diet, period, or dose of medication is right for their blood glucose level. Today, homecare technologies provide a new way of management for patients with chronic diseases by continuously monitoring their conditions using diagnostics and healthcare devices. Such systems typically have two units: a homecare unit on patient's home and a base unit in healthcare center. Vital bio-signals, like electrocardiograph (ECG), blood oxygen saturation (SPO2), native body index (NBI), and temperature, are transmitted to the base unit. The base unit in a healthcare center analyzes the patients' bio-signals and takes necessary actions as needed (Omuno et al. 2011). Homecare system offers many benefits. First of all, using a homecare system helps to reduce healthcare costs, such as reducing risk of overseeing the complications of chronic disease. Thus, long-term complications of diabetics can be avoided, which may affect the central or peripheral nervous system and give rise to nephropathy and neuropathy or cause blindness (Kim et al. 2008). Continuous monitoring of patients has the potential of decreasing risk of such complications remotely. In addition, homecare would also help minimizing the hospital stays and frequency of hospital visits and thus improving the quality of life. Shepperd and Iliffe (2005) pointed out in their study that even if the duration of hospital stay is not reduced much, allocation of care from hospital to home increased the overall time of care, which caused patient's greater satisfaction with care than those in hospital. Considering the demographic structure of Turkey, this technology could be beneficial in Turkish population as well. According to estimates for 2030, Turkey is likely to have demographic structure similar to European countries (Güvenç and Aktaş 2011), with the increasing elderly population and indices of chronic diseases.

Even though homecare technologies were perceived to be helpful in chronic disease management, there are few barriers in use. One of them is the resistance of patients to such technologies. In order to make effective use of homecare technologies, it is necessary to investigate patients' perception and the factors affecting their behaviors. In the literature, there are different models trying to reveal the aspects for acceptance of end user. Unified technology acceptance model (UTAUT) is one of these models (Venkatesh et al. 2003). UTAUT was used in many context; one of which was e-health. This study proposed a model for patient technology acceptance by taking UTAUT as a base model. The purpose of this study was (1) to identify contributions of applying of technology acceptance model during pre-design phase and (2) to identify the factors effecting the mobile homecare technologies and the perception of patients for mobile homecare technologies.

The paper was organized as follows: Sect. 13.2 presented background information of mobile homecare systems. In Sect. 13.3, research methodology of the study, formulation of homecare system model, the hypothesis, data collection method, and statistical analysis methods were described. Section 13.4 contained the statistical analyses of the data collected from patients with chronic diseases. All the steps of the statistical analyses were provided with details. Finally, the results of the analysis and hypothesis testing were shared. In Sect. 13.5, conclusions, discussion, limitations, and possible future work were given.

13.2 Background Information

13.2.1 Mobile Homecare Systems

13.2.1.1 Architecture

Patients with chronic diseases need a special way of health care. It is regular that such patients (i.e., elderly individuals) have more than one chronic disease. The size of this population is also growing causing a rapid growth in healthcare resource consumption. Moreover, the rate of hospitalization and prevalence of disability is also increasing among this group (Omuno et al. 2011).

Recent development in IT and medical sciences enabled establishing virtual care environment that assists for the needs of patients (Li and Istepanian 2003). Within the environment, named as homecare systems, patients could be assisted remotely, reducing the need for hospital visits (Angius et al. 2008). In addition, homecare systems provide patient-centric disease management in which patients have the opportunity to be involved in their disease management.

A homecare system has two separate sides: patient home and care center. In this system, patient's health data is delivered from one side to other. Figure 13.1 demonstrated these two parties of the system and their interactions. As the block diagram showed, the healthcare data delivery occurred from home unit to care center.

In this system, home unit is the supplier of the health data, and the care center is the destination. To maintain the data delivery, health data must be collected at the home side via measurement devices. In the system, patients perform, observe, and record vital signals via a measurement device. Each device has a specific purpose for one type of vital signal. Demonstration of these components was shown in Fig. 13.2.

Fig. 13.1 Homecare system block diagram

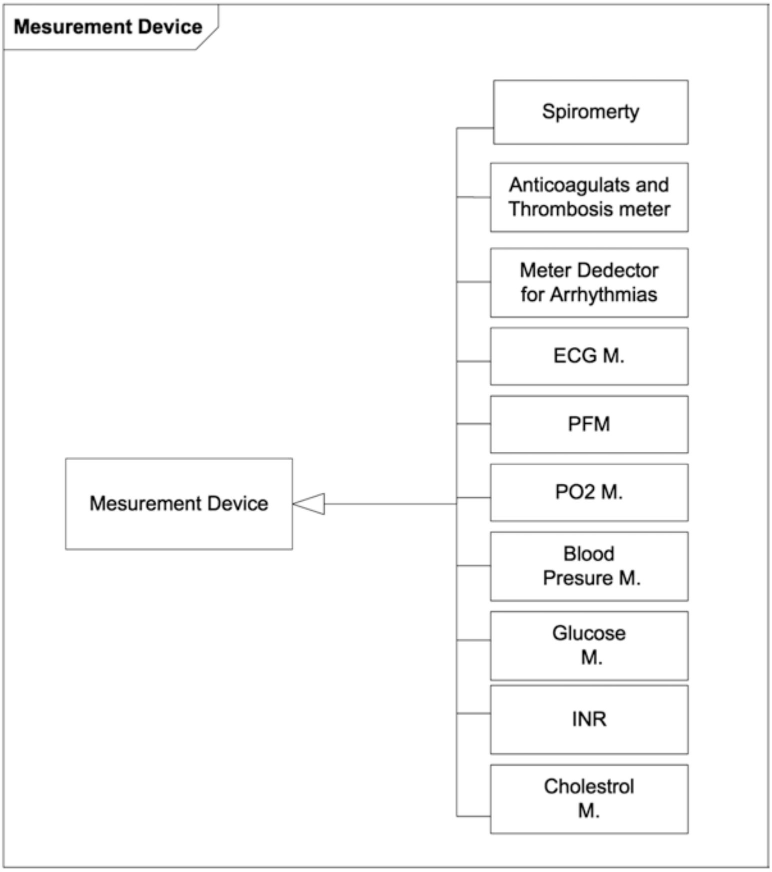

Fig. 13.2 Measurement device block diagram

The data collected via these devices are transported to the care center via a gateway. On the care center, patient's condition is analyzed. Based on the emergency level, feedbacks, alerts, and notifications are generated. This communication path is illustrated on the block diagram, Fig. 13.3.

13.2.1.2 Previous Studies

In the literature, there have been number of studies investigating homecare systems. Kim et al. (2008) proposed a system that a smartphone was used as a portable gateway. The gateway integrated bluetooth and code division multiple access network for communication. The messages transmitted to the main server in HL7 standard. Similarly, Korsakas et al. (2006) proposed a wireless ECG and motion activity

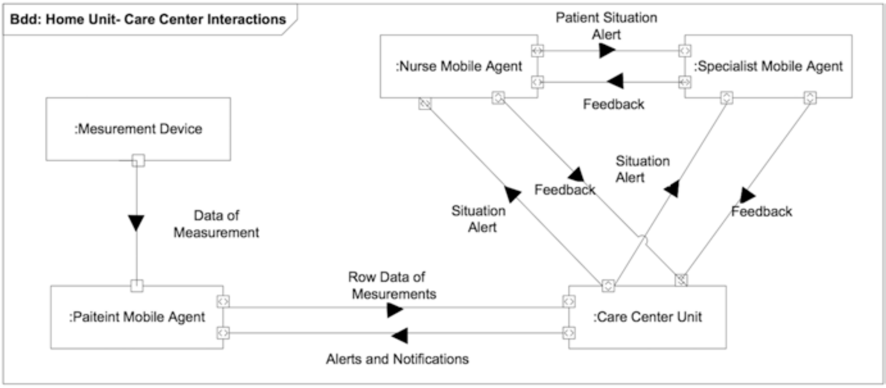

Fig. 13.3 Home unit-care center interactions

system developed for homecare patients. System was composed of a three-channel ECG recorder device with bluetooth module that communicates with the PC software that maintains real-time signal analyses and a warning mechanism. Software detected harmful situations for patient and sent a warning signal to the patient and also sent the results of analysis to physician.

The system presented by Li and Istepanian (2003) suggested a conceptual model for diabetics management program based on the third-generation mobile system, using agents for an environment that provides intelligent and personalized monitoring services to patients, best-practice decision support to physicians, and wellness maintenance for cost control. Ojesanmi et al. (2010) proposed a framework for a homecare system enabling health delivery to HIV/AIDS patients. The system was also based on 3G mobile technology using agents. The actors of the system were the agents in the system each of which used mobile phone to communicate with the server at anywhere and anytime without restrictions. Similarly, Koutkias et al. (2002) presented a multi-agent system that was integrated in homecare telemedicine system, which was functioning as a central contact point for patients with diabetic and congestive heart failure. The purpose of the system was to generate a mechanism sending alert or notifications based on patient's condition.

On the other side, Angius et al. (2008) proposed a system that was based on DVB-T technology, where patients interacted with the health-monitor device through a TV screen and the remote controller of the set-top box. System was defined as cost-effective and easy to use because it was built upon TV set which was easy to use by most patients and existed in every house. Lee et al. (2000) presented a homecare service system based on community antenna television (CATV) and RF modem. The service provides real-time and high-quality video and audio that supported interactive communication between the healthcare provider and patient. The RF modem that was part of the system provided transmission of vital body signals like ECG. Similarly, the PANACEIA-TV project was a homecare system

(Maglaveras et al. 2003) that enabled patients to monitor their health and to access health information and guidance. System was based on the DVB-S technology. Patients who suffered from adult congenital heart disease (ACHD) could be monitored from their home. The system also aimed to evaluate the attitude toward the use of new technologies such as interactive TV in remote health care for disease management.

In the study of Kyriacou et al. (2003), telemedicine unit was installed at patient's home, and the base unit was installed at the physician's office or hospital. Communication was performed by GSM mobile telecommunication network satellite links or plain old telephone service (POTS) links in collection of vital signals and still images. Using the system, doctor can monitor the patient at home. The paper by Lin et al. (2008) presented homecare solution implemented on ZigBee-based wireless device by integrating the biosensors to monitor the vital signals like body temperature, blood pressure, heart rate, and SPO2. The proposed homecare system created alerts if the vital data was abnormal and sent an email and a simple message to notice family members. Miao et al. (2006) took a further step ahead and proposed the design and implementation of a pervasive computing-based multimodal tele-home healthcare system. In the same manner, Traver et al. (2003) presented a homecare solution for patients with cardiac diseases. The system was available on platforms like personal digital assistant (PDA), set-top box (STB), laptop, and personal computer (PC). In the system, intensive homecare autonomous monitoring and home hospitalization scenarios were implemented. In this system, first of all, home intensive homecare was implemented as a synchronous service mainly for patients having surgical operations who need an intensive monitoring. Secondly, autonomous monitoring was created as an asynchronous service where the patient's vital bio-signals were monitored. Finally, home hospitalization unit created a scenario which provided a set of tools for medical staff to manage all of the patients visited daily.

The systems that were described above had two separate components as a base unit at the care center and a monitoring system at the patient's home. The monitoring system was where data was collected, and the base unit was where data was analyzed. In addition, all of the systems shared similar conceptual model. Li and Istepanian (2003) described this basic architecture of the system in a row scenario. In this conceptual model, patient vital signals were collected with measurement devices. The devices were specialized for vital signal type. Some of the parameters that can be observed are anticoagulants and thrombosis level, blood glucose level, electrocardiography (ECG), peak flow measurement of exhaled air, spirometry (lung capacity), blood oxygen pressure (level of INR), level of blood cholesterol, blood pressure, and body weight. The parameters listed above were collected using different measures and transferred to an access point at patient's home via communication protocols. The data was sent to the base unit at the healthcare center and analyzed at the care center for predicting possible urgent situations.

13.2.2 User Acceptance Researches on Mobile Homecare Systems

Mobile homecare systems, which promoted patient mobility and the well-being of the patient, have also been subject to user acceptance researches. In this study, to reach the studies of acceptance of homecare technologies, electronic databases of PUBMED, MEDLINE, and Google Scholar were searched. The findings were discussed in this section.

Or et al. (2008) explored the potential characteristics of health information technology acceptance among patients with heart disease. In the study, the relationships between several acceptance factors and intention to use and self-reported use were presented. Results indicated that higher healthcare knowledge was associated with increased acceptance; subjective norm and acceptance had strong relationship (i.e., patients were more likely to accept the web-based health technology if they thought that their important others); and perceived usefulness and perceived ease of use had positive influence on acceptance. It demonstrated that patients were more likely to accept the technology if they believed that the technology was useful and easy to use. Perceived ease of use was associated with perceived usefulness; perceived behavioral control was associated with increased acceptance and influenced by internal and external constraints like being able to use the technology and availability of resources; and perceived behavioral control was associated with self-reported use. Thus, patients, who believed that they had higher control and ability to use the technology, has tendency to use the technology. On the other side, Or and Karsh (2009) reported a systematic literature review of 52 research studies that aimed to identify variables promoting consumer health information technology (CHIT) acceptance among patients. This study was empirical with a substantive focus on quantitatively determining variables associated with acceptance of CHITs.

In another study by Or et al. (2011), factors affecting homecare patients' acceptance of a web-based interactive self-management technology were investigated. The author used UTAUT and integrated models to investigate the acceptance of a web-based and interactive self-management technology among homecare patients. Forty-eight of the 101 surveys were through phone interview, and 53 were via mail. Results presented that healthcare knowledge had no significant impact on behavioral intention, but it positively predicted perceived effective use. Perceived usefulness was the most important factor that explained a significant proportion of the variance in behavioral intention. Perceived ease of use had no significant direct effect on behavioral intention. It was explained as the users had knowledge to use a technology and ease of use of the technology becomes less salient. Perceived usefulness, healthcare knowledge, and behavioral intention were accounted for 68.5% of the variance in perceived effective use.

Wilson and Lankton (2004) proposed that patients' acceptance of provider-delivered e-health can be modeled by measuring the effects of several key antecedents to e-health use and by applying models of acceptance developed in the information technology field, conducting an online questionnaire with 163 participants. The study uses two theoretical models of IT acceptance, TAM and motivational model. Effectiveness of acceptance models and importance of antecedent factors were measured. Model fit was assessed using a set of metrics. All models showed good fit on particular metrics (goodness of fit, adjusted goodness of fit, comparative fit index, normed fit index, Tucker-Lewis index), whereas some were outside of target limits of other metrics' root mean square error of approximation. All of the acceptance models performed reasonably well in the tests. Authors also suggested that healthcare providers have flexibility in choosing which model to apply to e-health acceptance.

In the study by Chae et al. (2001), patient satisfaction with telemedicine in home health services for the elderly was studied, and the mobile systems were located in each patient's home. In this system, telemedicine system allowed the doctor and nurse to view patient medical record summary during the teleconferencing (tested with 50 randomly selected participants). Telemedicine was found effective in terms of reducing the number of clinic visits from 0.64 to 0.42 per month. Similarly, Liddy (2008) studied a tele-homecare system for patients with multiple chronic illnesses. The aim of the study was to examine the feasibility and efficacy of integrating home health monitoring into a primary care setting. Twenty-two patients were chosen from the experimental group of 120 patients with chronic illnesses and were identified as being at risk based on objective criteria and physician assessment.

Fortin (2005) investigated clinician acceptance of a guideline-based patient registry system for chronic disease management (tested with 17 participants). According to results of the study, the UTAUT analysis revealed that social influence, usefulness, and facilitating conditions were important variables for the acceptance of new technology. However, the issues like security certificate implementation, access and confidentiality, physician participation, data entry, flow sheets, infrastructure, and training were not explained by the model of UTAUT.

Study of Standing and Standing (2008) was about a mobile technology solution with 500 nurses, 600 homecare personnel, and 710 care aid workers about a homecare system. The research reported a pilot study where the mobile technology was tested with 50 nurses. Results showed that facilitating conditions were important criteria for technology adoption. Self-efficacy and computer anxiety had influence on acceptance. Improved communication, reduced costs, reduced errors, data acquisition, better patient care, better system load, cost-effectiveness, and leveraging expertise were reported as the benefits of mobile technology adoption. Lack of system integration; centralized system; high reliability requirement for patient care; conservatism; lack of expertise, training, and support; and security and privacy issues were found to be the barriers of mobile technology adoption.

Cranen et al. (2011) explored patient's perceptions regarding prospective telerehabilitation services and the factors that facilitate or impede patients' intentions to use these services. The study related patient perceptions of prospective home by using the UTAUT as the theoretical model. The themes were quality of feedback, fellow sufferer contact, and transition knowledge. The results showed that alienation had influence on performance expectancy. Ease of use had effect on effort expectancy, and physician influence and partner influence had an effect on social influence.

Treatment motivation, flexibility of exercise times, travel issues, availability of resources, and social isolation had influence on facilitating conditions.

Chiu et al. (2004) studied usage and non-usage behavior of e-health services among Chinese-Canadians having a family member with dementia. In addition to technology acceptance, the study focused on intention to use and patterns of usage. According to results of the study, effort expectancy, performance expectancy, and perceived caregiver burden had influence on intention to use. Perceived caregiver burden had influence on initiation of use. The items that had influence on frequency of use were age, gender, education, year of immigration, years of care, hours of care, relationship with care-recipient, care-recipient functioning level, care-recipient problem behavior frequency, caregiver reaction to problem behaviors, caregiver perceived burden, self-rated health, and attitude toward technology.

13.3 Methods

As reported in the previous section, technology acceptance studies for homecare systems were generally conducted on complete system. This study aimed to apply such acceptance models on pre-design phase of system development. In order to achieve this goal, a "Homecare System Model" was formulated. This model was based on the aforementioned systems and studies in the section of background information. After the formulation phase, research model for study was developed based on UTAUT. Finally, research material was composed by using technology acceptance literature.

13.3.1 Formulation of Homecare System Model

In order to formulate a model for homecare system, it is necessary to define homecare system components and features. Existing homecare system models on literature were analyzed to identify specification of the system. Then, System Modeling Language (SysML) was used in block diagram stretches to model specifications of the system. After all, requirements of the homecare system were identified, and a paper-based prototype of the system was produced.

13.3.2 Formulation of Research Technology Acceptance Model

On section Formulation of Homecare System Model homecare system model is formulated. In this second formulation step, proposed acceptance model for the study was explained.

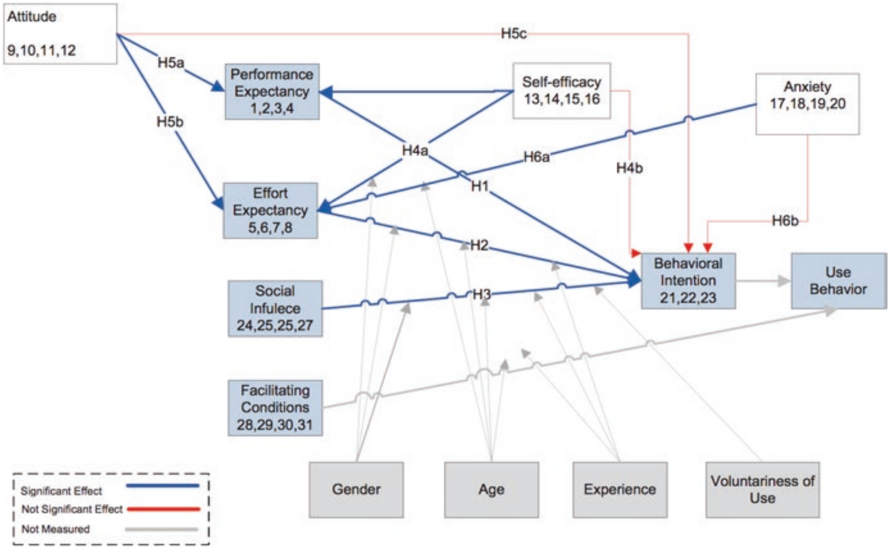

Fig. 13.4 Study model

The proposed model was configured based on the theoretical model of UTAUT. In the study of Venkatesh et al. (2003), seven constructs found significant for behavioral intention or usage behavior. Four of these constructs were performance expectancy, effort expectancy, social influence, and facilitating condition. They were categorized as direct determinants. The remaining three of the constructs, attitude toward using technology, self-efficacy, and anxiety, were not modeled as direct determinants. Instead, self-efficacy and anxiety were qualified as fully moderated by effort expectancy. In the same point of view, the effect of attitude toward using technology was formulated to influence effort expectancy and performance expectancy. These relationships were listed as indirect determinants of intentions and usage behaviors.

In this study, it was investigated whether the user behavior in the chronic disease management environment with mobile home care system can be explained with the prototype still in the preliminary design stage. The study model was given in Fig. 13.4 (Fig. 13.5).

The four main constructs of the UTAUT, performance expectancy, effort expectancy, social influence, and facilitating condition, have been previously explained in the literature section. However, the indirect determinants tested within the study remained. In that regard, attitude toward technology was defined as an individual's overall effective reaction to using a system (Venkatesh et al. 2003). It was represented by different names in the literature. Anxiety was defined as "the fear experienced when interacting with a computer or anticipating an interaction" (McDonald 2002). Self-efficacy was defined as "the belief an individual has in his/her ability to successfully perform a certain behavior" (Fagan et al. 2004).

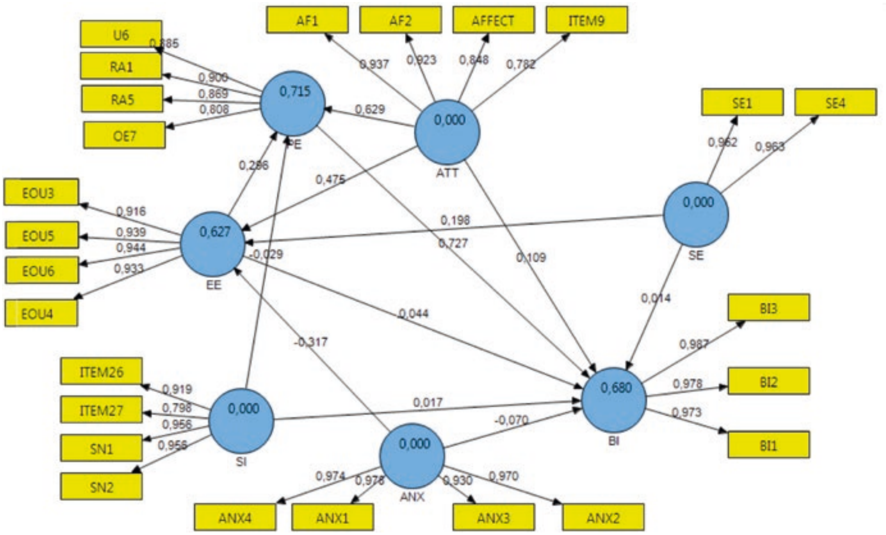

Fig. 13.5 Measurement model by PLS algorithm

13.3.3 Hypotheses

This study aimed to perform user acceptance tests based on the model proposed as explained in pervious paragraphs about the pre-design phase prototype. Since, the system in this study was not available yet, use behavior was not tested based on the prototype systems. Due to this limitation, the model was able to investigate the determinants related to the perceptions toward behavioral intention. So, the relationship between use behavior and facilitating conditions was not hypothesized. The following are the hypotheses of the study:

- H1 Performance expectancy (PE) will have positive effect on the behavioral intention of the mobile homecare system users.
- H2 Effort expectancy (EE) will have negative effect on the behavioral intention of the mobile homecare system users.
- H3 Social influence (SI) will have positive effect on the behavioral intention of the mobile homecare system users.
- H4a Self-efficacy (SE) will have negative effect on the effort expectancy of the mobile homecare system users.
- H4b Self-efficacy (SE) will not have significant effect on the behavioral intention of the mobile homecare system users.
- H5a Attitude (AT) will have positive effect on the performance expectancy of the mobile homecare system users.
- H5b Attitude (AT) will have positive effect on the effort expectancy of the mobile homecare system users.

- H5c Attitude (AT) will not have significant effect on the behavioral intention of the mobile homecare system users.
- H6a Anxiety (ANX) will have negative effect on the effort expectancy of the mobile homecare system users.
- H6b Anxiety (ANX) will not have significant effect on the behavioral intention of the mobile homecare system users.

13.3.4 Instrument Development

For the data collection phase of the study, a questionnaire was used as the quantitative research instrument. UTAUT research items were used for the development of questionnaire.

Since the system that was analyzed in terms of user technology acceptance was not available yet, there was a need to demonstrate the materials for the system. Moreover, target user group of the system were the patients with chronic diseases who were mostly elder people. Thus, distributing online or paper-based questionnaire would not be effective to collect representative responses. Therefore, face-to-face interview method was used to collect questionnaire responses. It was found more suitable for this study considering the target group. The user interface prototypes that were previously developed were used as the supplementary material for interview to present the system architecture. This presentation step was prepared consistent with the use cases which were previously discussed. System design and screen prototypes were reviewed with two specialists in order to validate prototypes to be consistent with healthcare literature. The specialists helped to create a sample scenario including INR level, blood glucose level, ECG, and spirometry measurements. The scripts of the scenario were written.

The items used in the questionnaire were translated from English to Turkish. The translated form of questions was reviewed by six adults in order to test understandability and clearness of questionnaire items. The necessary revisions were made according to their recommendations. The questionnaire was prepared in two parts. The first part included the demographic questions. It included age, gender, education, computer usage, and chronic disease status. The second part of the questionnaire included the questions based on UTAUT items. Responses for the questionnaire items were collected using 5-point Likert scale. The scale responses were listed from 1 to 5 (5, totally agree; 4, agree; 3, indecisive; 2, disagree; 1, totally disagree). The demographic questions and survey items were provided in Appendix.

Since the study required participation of individuals, ethical approval was required in order to collect data from the participants. The Research Center for Applied Ethics at METU approved the questionnaire, and ethical approval was granted before the research.

Table 13.1 Demographics

	Type	%
Gender	Male	37.25
	Female	62.75
Age	50–65	72.55
	>65	33.33
Chronic diseases	1	7.84
	2	70.59
	More than 2	21.57
Experience on homecare system	Yes	0.00
	No	100.00
Technology experience	Not exists	19.61
	Beginner	76.47
	Good	3.92
Disease types	COPD	3.92
	Diabetes	23.53
	Asthma	0.00
	Hypertension	31.37
	Coronary heart disease	39.22
	Arrhythmias	9.80
	Fat metabolism	29.41
	Cancer	3.92
	Others	3.92

13.3.5 Study Sample

The target group of this research was the patients with chronic diseases. The study was conducted in two independent samples that have characteristics of this target group: pilot study and main study. The aim of the pilot study was to test the reliability of the selected questionnaire items, before conducting the main study.

Pilot study was conducted with 20 participants (9 male, 11 female). The participants were selected by snowball approach. In the main study, there were 51 participants (32 male, 19 female). Participants were required to have at least one chronic disease. The participation of the study was completely based on voluntariness. The demographics of the sample in the main study were provided in Table 13.1.

13.3.6 Data Analysis

Since our sample size was small, the statistical analysis method that fits within the study sample was identified as structural equation model (SEM). SEM was one of the statistical methods that was widely implemented in the studies in information systems. SEM was described as a statistical technique that was used to test or estimate cause-effect relations. There were two types of SEM, covariance-based (CB-SEM) and partial least square (PLS-SEM)[1]. Covariance-based SEM had limitation on sample size. In order to apply this type of SEM, item/sampling ratio was recommended to be 1/10 or more. This type of SEM also required a normal distribution. On the other hand, PLS-based SEM was more suitable for data with small sample size and does not require normal distribution. Thus, PLS-based SEM was selected for the analysis of this study.

The testing was initiated with reliability analysis using Cronbach's alpha. Coefficient of reliability helped to measure internal consistency. Missing data analyses and outlier analyses were also conducted. SPSS 17.0 was used for reliability test, missing data analyses, and outlier detection. The data has been optimized for subsequent analysis of SEM. After descriptive analysis, PLS-SEM was performed. The guidelines for PLS-SEM was followed during the analysis (Genef and Straub 2005; Haenlein and Kaplan 2004). SmartPLS was used for PLS analysis (Ringle et al. 2005). The results of data analysis are presented in the next chapter.

13.4 Results

In the data set, no missing value was recorded. Hence, there was no need to incorporate any missing data handling method. Reliability analysis suggested deleting of some of the items in order to increase total factor's Cronbach's alpha. Removing A1 item of attitude, SE6 item of self-efficacy, and ANX3 item of anxiety constructs increased the Cronbach's alpha from 0.8 to 0.9. For three such cases, item total Cronbach's alpha values were between or above the good (0.8–0.9) range. In addition, there was not a significant increase in the initial Cronbach's alpha when deleted. On the other hand, for SE6 item of self-efficacy construct, Cronbach's alpha increased from 0.726 to 0.820, and the interval of consistency was increased from acceptable (0.7–0.8) range to good range (0.8–0.9). Thus, the item SE6 was removed. In order to identify if there were any outliers to handle, mean and 5% of trimmed mean were observed. For all items, there was not a significant difference between these two values. Therefore, it was decided that there were no outliers in the data set, and hence there was no need to correct/delete items for the further analysis.

[1] https://www.smartpls.com/documentation/learn-pls-sem-and-smartpls/pls-sem-compared-with-cbsem.

13.4.1 PLS Algorithm

After completing descriptive statistical analyses, the data was imported to SmartPLS, and the path model was created. The measurement model was created by running PLS algorithm. The validity of constructs was investigated by checking convergent validity and discriminant validity (Haenlein and Kaplan 2004).

Convergent validity was defined as a measure of correspondence or convergence between similar constructs (William 2008). In PLS, in order to investigate convergent validity, the average variance extraction (AVE) scores, reliability, and the outer loading were analyzed. In that regard, the results met the requirements. The outer loadings (factor loadings) were greater than 0.7, the AVE scores were equal or greater than 0.5, and composite reliability values were greater than 0.7. The discriminant validity was defined as a metric to show that each construct is different than the others (William 2008). In order to test the discriminant validity, the AVE squared root and the outer loadings of each indicator were analyzed (Genef and Straub 2005). The square roots of AVE values were greater than the other correlation values among the constructs. The results proved that all the items met the requirements.

13.4.2 Hypothesis Testing

In order to create the structural model, bootstrapping algorithm was run on SmartPLS. T-Statistic was tested for each path, in order to investigate the relations between latent variables. The significance value of p was considered in determining significant relationships. The latent variable relationships at significance level 99% ($p < 0.001$), 95% ($p < 0.05$), and 90% ($p < 0.1$) were identified. These results of hypothesis testing were listed in Table 13.2. Significant and nonsignificant relationships were reported.

According to results of PLS analysis, positive significant relation ($p < 0.05$) was found between performance expectancy and behavioral intention. Therefore, hypothesis H1 was supported. There was positive nonsignificant relation between effort expectancy and behavioral intention. Because H2 mentions the directions of relation not the significance, Hypothesis H2 was not supported due this positive effect. Similarly, social influence had a positive nonsignificant effect on behavioral intention. Because H3 also mentions the directions of relation not the significance, Hypothesis H3 was also not supported due this positive effect. These findings were not supporting the significant relationships of Venkatesh et al.'s (2003) study.

Positive significant relation at $p < 0.05$ was found between self-efficacy and effort expectancy. Thus, H4a was supported. Moreover, the relationship between self-efficacy and behavioral intention was not significant, and H4b was not supported. Positive significant relationship at $p < 0.05$ was identified between attitude and effort expectancy. Therefore, H5b was supported. Similarly, the relationship between attitude and performance expectancy was positively significant, which supported H5a.

Table 13.2 Results of hypothesis testing

Hypothesis	Related path	Path coefficient	T-Statistic	*P* value	Result	
H1	Performance expectancy (PE) will have positive effect on the behavioral intention of the mobile homecare system users	PE-> BI	0,727,411	3,325,118	0.002**	S
H2	Effort expectancy (EE) will have positive effect on the behavioral intention of the mobile homecare system users	EE-> BI	0,044113	0,236,442	0.41	N
H3	Social influence (SI) will have positive effect on the behavioral intention of the mobile homecare system users	SI->BI	0,017379	0,149,967	0.44	N
H4a	Self-efficacy (SE) will have positive effect on the effort expectancy of the mobile homecare system users	SE->EE	0,198,256	2,351,834	0.01**	S
H4b	Self-efficacy (SE) *will not have* significant effect on the behavioral intention of the mobile homecare system users	SE->BI	0,014264	0,141,588	0.444	N
H5a	Attitude (AT) will have positive effect on the performance expectancy of the mobile homecare system users	AT->PE	0,628,935	6,245,197	0.000***	S
H5b	Attitude (AT) will have positive effect on the effort expectancy of the mobile homecare system users	AT->EE	0,474,874	3,524,448	0.001**	S
H5c	Attitude (AT) *will not have* significant effect on the behavioral intention of the mobile homecare system users	AT->BI	0,109,068	1,006479	0.17	N
H6a	Anxiety (ANX) will have negative effect on the effort expectancy of the mobile homecare system users	ANX->EE	−0,3175	2,333,827	0.01**	S
H6b	Anxiety (ANX) *will not have* significant effect on the behavioral intention of the mobile homecare system users	ANX->BI	−0,06982	0,73,139	0.23	N

S Supported, *N* Not supported
** $p < 0.05$, *** $p < 0.001$

Moreover, the relationship between attitude and behavioral intention was not significant, H5c was not supported. Negative significant relationship at $p < 0.05$ was found between anxiety and effort expectancy. Thus, H6a was supported. The relationship between anxiety and behavioral intention was not significant, so H6b was not supported. Finally, although it was not hypothesized, a positive significant relation was found between performance expectancy and effort expectancy.

13.5 Discussion

In this study, the factor affecting the acceptance of mobile homecare system was investigated. The model was developed by employing UTAUT as the theoretical model. The main finding this study was that the implementation of an UTAUT model for a homecare. Furthermore, the perceptions of the participants were collected since the system was not available yet. According to results of the measurement and structural model of PLS-based SEM, most of the hypotheses were supported. The results were discussed in this section.

Venkatesh et al. (2003) identified performance expectancy as a strong predictor of behavioral intention. In our study, performance expectancy was also the most significant factor at $p = 0.001$. Therefore, inference of Venkatesh et al. (2003) was also supported by our study. This relation implied that as the performance expectancy increases, the patients become more likely to use the system. From this point of view, we can conclude that when participants believe that system usage will help them in chronic disease management, they would intent to use the system.

According to the results of our study, attitude was a significant predictor of performance expectancy. These results showed that if overall attitude of patient toward mobile system was positive, then they were more likely to find the system helpful for chronic disease management. Venkatesh et al. (2003) also tested this effect of attitude on the performance expectancy and found that "influence of attitude toward using technology is non-significant on intention due to its being captured by process expectancy and effort expectancy." Our study also showed that the effect of attitude was not significant for intention of patients to use the mobile homecare system. Thus, it can be concluded that the results are consistent with Venkatesh et al. (2003), and the effect of attitude was captured by performance expectancy.

On the other side, effort expectancy was affected by self-efficacy, attitude toward using technology, and anxiety constructs. First of all, there was a positive significant relation between effort expectancy and self-efficacy. Furthermore, the effect of self-efficacy was nonsignificant over behavioral intention. This result was consistent with Venkatesh's et al. (2003) study, which stated that "the effect of self-efficacy over behavioral intention is nonsignificant due to its being captured by effort expectancy." This result also implied that if the patient's belief on his/her individual abilities were at the degree of performing a certain behavior successfully, then the system became easier to use. Moreover, while the effect of attitude toward using technology over effort expectancy was positively significant, it was nonsignificant over behavioral intention. This result was matching with Venkatesh et al. (2003), which stated that "attitude toward using technology is nonsignificant due to its being captured by process expectancy and effort expectancy." Moreover, the positive significant relation implied that if the patient overall attitude for using the technology increases, the degree for ease of use also increases. Finally, while the effect of anxiety over effort expectancy was significant, it was nonsignificant over behavioral intention. This result was also consistent with Venkatesh et al. (2003) hypothesis. The negative significant result between effort expectancy and anxiety meant that if patient had a fear of using the mobile homecare system, he/she would find the system less easy to use.

In this study, in contrast to Venkatesh's et al. (2003) findings, the relation of the effort expectancy with behavioral intention was surprisingly nonsignificant. On the other hand, there was a positive significant path, which was not hypothesized, between effort expectancy and performance expectancy. So, the effect of effort expectancy might have been captured by performance expectancy for mobile homecare system. Or et al. (2011) used UTAUT as theoretical base in their study on factors affecting homecare patient acceptance of a web-based interactive self-management technology. They also found significant path between perceived usefulness (performance expectancy) and perceived ease of use (effort expectancy). From this point of view, our finding was also consistent with the literature.

The influence of social influence on behavioral intention (p = 0,44) was not at significant level. According to prior research of Venkatesh and Davis (2000), social influence is found to be significant in mandatory settings. In our study, the proposed system was not a mandated system. Thus, it was justified that for social influence it was normal to be nonsignificant determinant. So, this nonsignificant result was also consistent with Venkatesh et al.'s (2003) findings.

In the bottom line, the study revealed that patients may intent to use the system because they believed that using the (proposed) mobile homecare system can be helpful for them. About 66% of participants had found the system useful. However, about 64% of participants provided low scores to effort expectancy, which meant that these patients did not found the system easy to use. So, the behavioral intention could be increased by promoting system's ease of use. According to these results, the proposed systems could be revised to promote ease of use. At this level, such a revision would be easier than for an in-use system. For most of the systems, such the acceptance models were applied after the system has been released. After that phase, making change on the system might be more difficult requiring more time/effort and expenditures.

13.6 Conclusion

The study provided empirical data for implementation of UTAUT in the system design phase. From this point of view, this study also provided experimental results for the homecare systems that will be developed in the future work. According to the structural model (regarding path coefficients, T values, significance level, and variance explained), the model was able to explain 68% of the total variance (R2) of behavioral intention to use the proposed mobile homecare system. Our study also showed that, for systems at the design level, the acceptance models can also be used for pretesting the concept, and it may give valuable insight with high variance. This study also provided empirical data about the perception of patients with chronic diseases for mobile homecare system. The main study limitations were (1) small sample size, (2) the need for interview method in order to collect data (which affected the increased data collection time and limited sample size), and (3) using an unavailable system.

In the future, it is necessary to extend this study with a larger sample size. In addition, disease-specific analysis was also suggested. Moderators of UTAUT (like age, gender) were not addressed within this study. Thus, moderator-specific analyses are suggested with large samples. In addition, to draw more specific conclusions, this study can be repeated with longitudinal method and employing more than one group of participants having different demographic background.

Appendix

13.6.1 Demographic Questions

Age	<25 26–35 36–49 50–65 >65
Gender	Male Female
Education	Elementary school High school University Master PhD
Diseases	COPD Diabetes Asthma Hypertension Coronary heart diseases Arrhythmias Cholesterol Other
Frequency of hospital visits	1 or 2 times per year 1 time per 3 months Each month More than 1 per month

(continued)

How many times have you stay in a hospital since past 1 year?	Never 1 More than 1
Select the measurement devices you use	Blood pressure Blood glucose meter EKG INR meter The heart's activity Anticoagulants and thrombosis level PO2 meter
Have you ever heard about homecare systems?	Yes No
(6) Chose the level of experience for using technologies like computer, smartphone	None Beginner Average Expert

13.6.2 Items of the Survey

Performance expectancy	I would find the system useful in my job
	Using the system enables me to accomplish tasks more quickly
	Using the system increases my productivity
	If I use the system, I will increase my chances of getting a raise
Effort expectancy	My interaction with the system would be clear and understandable
	It would be easy for me to become skillful at using the system
	I would find the system easy to use
	Learning to operate the system is easy for me
Attitude toward tech.	Using the system is a bad/good idea
	The system makes work more interesting
	Working with the system is fun
	I like working with the system
Self-efficiency	I could complete a job or task using the system, if there was no one around to tell me what to do as I go
	I could complete a job or task using the system, if I could call someone for help if I got stuck
	I could complete a job or task using the system, if I had a lot of time to complete the job for which the software was provided
	I could complete a job or task using the system, if I had just the built-in help facility or assistance

(continued)

Anxiety	I feel apprehensive about using the system
	It scares me to think that I could lose a lot of information using the system by hitting the wrong key
	I hesitate to use the system for fear of making mistakes I cannot correct
	The system is somewhat intimidating to me
Behavioral intention	I intend to use the system in the next months
	I predict I would use the system in the next months
	I plan to use the system in the next months
Social influence	People who influence my behavior think that I should use the system
	People who are important to me think that I should use the system
	The senior management of this business has been helpful in the use of the system
	In general, the organization has supported the use of the system

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Part IV
Global Perspectives and Issues with mHealth

Chapter 14
Improving Access to Health Services in Sub-Saharan Africa Using Mobile and Wireless Technologies

Emmanuel Eilu

14.1 Introduction

In sub-Saharan Africa, communicable sicknesses are still the leading cause of death, causing about 70% of deaths (IPIN 2012). WHO (2016) reports that sub-Saharan Africa accounts for about 90% of the world's yearly 300–500 malaria cases. The most affected are children and pregnant women. Furthermore, with just about 12% of the world's population, sub-Saharan Africa accounts for 49% of maternal mortality and about 50% of infant mortality under age 5 years (Soucat 2014). Additionally, a sub-Saharan African population is the most affected with HIV and AIDS epidemic in the world. For example, in 2013, 71% (about 24.7 million) of the people living with HIV globally were from sub-Saharan Africa, with 1.5 million new HIV infections and 1.1 million AIDS-related deaths every year (UNAIDS 2014). On the other hand, viral hemorrhagic fevers (VHF) are steadily gaining ground in sub-Saharan Africa, with frequent occurrence of epidemics such as yellow fever, the Ebola virus, Marburg virus, Rift Valley fever, or Congo-Crimean hemorrhagic fever virus (IPIN 2012). The recent Ebola epidemic in the West African countries of Liberia, Guinea, and Sierra Leone is the gravest in history. It is reported that, out of 13,500 Ebola cases, about 4900 resulted in deaths (WHO 2016). Despite the massive disease prevalence, there are extremely few medical facilities and professionals to handle the disease burden. In many sub-Saharan African countries, there are very few hospital beds, doctors, nurses, midwives, and other health professionals as compared to their counterparts in developed countries. For instance, in 2009, on average, there were 62 hospital beds per 10,000 people in Europe, while sub-Saharan Africa had only 9 hospital beds per 10,000 people (WHO 2012; Vishwanath et al. 2012). The significantly low doctor to patient ratio has also been

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E. Sezgin et al. (eds.), *Current and Emerging mHealth Technologies*,
https://doi.org/10.1007/978-3-319-73135-3_14

reported in sub-Saharan Africa. For instance, the number of doctors per 10,000 patients in sub-Saharan Africa was 2.3 in 2010, while in Europe and the Americas, it was 33.3 and 22.5, respectively (WHO 2012; Vishwanath et al. 2012). The huge disease burden coupled with the weak health systems incapable of handling the disease burden has significantly affected the rate of economic growth and development. Sub-Saharan African countries and many economies in the Indian Ocean countries will be unable to develop unless there are massive investments from governments into their healthcare sectors (WHO 2016; IPIN 2012). The United Nations 2008 report on the steps so far made in achieving the Millennium Development Goals (MDGs) shows that there are still recurrent dreadful situations in the health sectors of many sub-Saharan African countries.

There have been numerous calls for measures that can improve health systems and curtail deaths caused by easily preventable diseases in sub-Saharan Africa. Various approaches have so far piloted. One of the approaches that have registered some success is the use of mobile technology to provide the much-needed health services, which is popularly known as mobile Health (mHealth). WHO (2011) defines mHealth as “the practice of medical and public health supported by mobile technologies, such as mobile phones, patient monitoring devices, personal digital assistants (PDAs), and other wireless devices” (p. 6). Kahn et al. (2010) define mHealth as “the use of portable electronic devices for mobile voice or data communication over a cellular or other wireless network of base stations to provide health information” (p. 255). For a case like in sub-Saharan Africa which has extremely weak health systems, high mortality rates, and very high prevalence of tropical diseases, the use of mobile technologies for providing the much-needed medical services has been recognized as a more cheaper and easier way to reach higher-quality health services at lower costs, thus lowering the mortality rates (Crul 2014). Some scholars have discussed the viability and the potential benefits of using mobile and wireless technologies. For instance, personal digital assistant (PDA) and mobile phone have been used for health-related research as creating awareness and adherence support and providing public-based social and health services (WHO 2011; Ogunmefun et al. 2010; Seebregts et al. 2009; Skinner et al. 2007; Tomlinson et al. 2009). All these researchers reveal that the use of mobile technology in providing health services has a great potential in providing critical health-related information even to the most distant settlements, and this can as well serve as an access point of national health surveillance systems. However, there is very little mHealth-based empirical evidence on the efficacy, sustainability strategy, and best practice, as the use of mobile technologies in providing health services remains dominant only in Europe, in the Americas, and in the Asian Tigers. Many of the mHealth projects implemented in sub-Saharan Africa are still at pilot or informal stages (Soucat 2014; Unite for Sight 2015).

14.2 Purpose of the Study

This chapter seeks to establish the extent to which the use of mobile and wireless technologies in the prevention, surveillance, management, and compliance of disease epidemic in sub-Saharan Africa addresses the rampant challenges associated with access to health services. This chapter also outlines and discusses bottlenecks hampering the successful implementation of mHealth in sub-Saharan Africa. Recommendations to these bottlenecks are also identified. The lessons outlined in this chapter may be valuable in informing governments in sub-Saharan Africa and other developing countries on the opportunity provided by the explosive spread of mobile and wireless technology as a tool for providing the much-needed health services.

14.2.1 Research Questions

Three major research questions were asked in this chapter:

1. To what extent do mobile and wireless technologies address significant challenges in the areas of disease prevention, surveillance, management, and compliance in sub-Saharan Africa?
2. What are the major challenges affecting the deployment of mobile and wireless technologies in the health sector in sub-Saharan Africa?
3. How can these bottlenecks be addressed?

14.3 The Methodology

A systematic review method was used to answer the three research questions identified in section "Research Questions".

14.3.1 The Need for Systematic Review

A systematic review was the primary method used in this chapter. In the last 30 years or so, some scholars have criticized narrative literature reviews style, observing that it is biased and inadequate regarding the thoroughness of research performed (Hemingway and Brereton 2009). This has led to the emergence and widespread use of systematic review method of research. Systematic review is a laborious method used to plot out secondary data and lets the evidence to emerge out automatically (DFID 2013). Its strength is in using empirical evidence to establish what works and how it worked (Zanker and Mallett 2013). Systematic review has been widely used for many years in different fields such as medical research and natural sciences. It is commonly used by international agencies such as the Australian Agency for International Development (AusAID), the UK's Department for International Development (DFID), and many others, and these agencies have funded a number of systematic reviews with the sole aim of finding what works and how it worked in generating development outcomes (Zanker and Mallett 2013). Please see the appendix for the reviewed literature in this chapter.

14.3.2 Systematic Review Method

In 1984, Cooper (1984) proposed a five-stage systematic review process, and it was followed by this chapter.

- Problem formulation – Apparent problem and research questions to be addressed by the review (Khan et al. 2003). This chapter formulated three major questions (see section "Research Questions") that needed to be answered or investigated using systematic review.
- Data collection – This normally takes the form of identification of relevant works. Guided by the three research questions stated in section "Research Questions", an extensive and unbiased literature search was conducted particularly on the extent to which mobile and wireless technologies have offered the much-needed services in the areas of disease prevention, surveillance, management, and compliance in sub-Saharan Africa and also the challenges and remedies of deploying mobile technology in health. A review was conducted on reports, journals, conference proceedings, books, and websites. Google Scholar was majorly used in this review. About 83 citations were selected for the review. Their potential relevance in the areas of prevention, surveillance, management, and compliance of different diseases was examined, and about 16 citations were removed because they were irrelevant. The remaining 67 citations gave relevant information on the three research questions.
- Data evaluation – Assessing the studies for inclusion in the review. This chapter used a simple data extraction table which was used to organize the information extracted from each review (e.g., authors, publication year, abstract, study design, and particularly the outcomes of these studies).
- Analysis and interpretation – Narrative synthesis was the primary form of analysis used in this chapter. It relies primarily on the use of homogenous words and text to summarize and explain the findings of the synthesis. From each of the studies, a homogenous trend was derived particularly on prevention, surveillance, management, and compliance of diseases in sub-Saharan Africa using mHealth.
- Public presentation – The findings of the review were presented in the next section. These findings majorly answer or address the three research questions stated in section "Research Questions".

14.4 Findings

As already discussed in the introduction, health challenges present perhaps the most substantial hurdle to sustainable global development in many sub-Saharan African countries. In the next section, this chapter discusses the potential of using mHealth to improve health services in sub-Saharan Africa.

14.4.1 Mobile Technology in Sub-Saharan Africa

Brinkel et al. (2014) observe that the application of mHealth services can transform global health systems. This assertion is supported by a powerful combination of four facts: (a) rapid technological growth, (b) the continued fall in the price of the mobile technology products, (c) widespread ICT infrastructure, and (d) wide spread use of mobile phones worldwide (Piette et al. 2012). The widespread adoption and use of mobile and wireless technologies are evident in many sub-Saharan African countries. Mobile penetrations in Africa, Asia-Pacific, and Latin America were expected to increase to 82%, 98%, and 119%, respectively, in 2014 (Vishwanath et al. 2012). In Uganda, for example, there are over 19 million mobile phone users, 2300 base stations, and 100% network coverage (UCC 2015). Mobile phones are and will remain the primary medium of telecommunication in sub-Saharan Africa and can be an alternative channel for health service provision (Lallana 2007). Therefore, the viability of mobile technologies supporting the much-needed health sector systems in sub-Saharan Africa is bigger than ever before. Some sub-Saharan African countries are already using mobile and wireless technologies in the health sector like monitoring measles outbreaks in Zambia, auxiliary diagnosis and treatment in Mozambique, and sending awareness messages in Benin, Malawi, and Uganda (Aker and Mbiti 2010). In Kenya, Malawi, and South Africa, mobile phones are being used to send several reminders a day to HIV-positive patients (Aker and Mbiti 2010).

14.4.2 mHealth in Sub-Saharan Africa

The pace at which mobile and wireless technologies have spread universally is matchless in the history of technology. In recent years, a significant influx into the healthcare industry by both private, nongovernmental organizations (NGOs), and government agencies particularly to offer mHealth services has been registered. Recent predictions suggest that the global mHealth market will grow to 24 billion US dollars by 2018, up from 4.5 billion US dollars in 2012 (Vishwanath et al. 2012). One of the biggest benefits that mobile and wireless technologies offer is the bridging of geographically spaced regions, where the infrastructure connecting the regions is extremely poor (Crown Agents 2014). With the introduction of mobile technologies, remote areas can now easily access professional medical services which were previously inaccessible to them or only accessible following a challenging, lengthy, and time-consuming journey. The potential benefits that these mobile technologies have created in tackling health challenges in sub-Saharan Africa have been enormous, the reason why medical bodies, NGOs, governments, and other players in the health sector have greatly embraced it (Crown Agents 2014). The mHealth projects are already being implemented enormously all over the world, but the projects are majorly gaining ground throughout sub-Saharan Africa, where demonstrations have been done in prevention, surveillance, management, and compliance of disease epidemics such as HIV/AIDS, malaria, Ebola, and much more. In the next section, this chapter discusses how the use of mobile and wireless technologies has tremendously aided the prevention, surveillance, management, and compliance of different diseases in sub-Saharan Africa.

14.4.3 Prevention

There is overwhelming evidence that prevention and control of noncommunicable diseases (NCDs) has proven to be one of the major barriers for the health sector in many sub-Saharan countries and even some middle-income countries (WHO 2013; Gaziano et al. 2007; Abegunde et al. 2007). Therefore, a number of carefully planned health awareness approaches together with multi-sectoral policies aimed at advocating for healthy lifestyles are much needed to decrease the burden of these NCDs (Gaziano et al. 2007; WHO 2013). One of the strategies that have been adopted by a number of sub-Saharan African countries is disease prevention through public health promotions. Health promotion and awareness campaign programs focus on keeping people healthy and encourage individuals in the communities to live healthy lifestyles. These strategies further focus on behavioral change so as to reduce the risk of contracting diseases and other morbidities. Some of these strategies include communication, education, and policy change. Both Wakefield et al. (2010) and Naugle and Hornik (2014) do acknowledge that while health awareness programs disseminated through television and radio can promote healthy living, there are quite a number of limitations to these traditional media. Some of these limitations include:

- Challenges in capturing audiences' attention in a multimedia environment.
- The one-way communication from the radio/TV to the listener.
- Mass broadcast, therefore it is difficult to target a particular audience.

Therefore, to solve some of these challenges identified, social media technologies have been introduced and used in a number of sub-Saharan African countries (Yepes et al. 2016). These social media technologies such as text messages (SMS), WhatsApp, Facebook, Twitter, and Instagram are increasingly being used in health awareness campaigns, providing target-specific messages that encourage specific behavioral changes like increased fruit and vegetable consumption (Silva et al. 2015), smoking cessation (ITU 2013), and adoption of healthy living and lifestyles (Beratarrechea et al. 2015). For example, since 2006, a number of mobile phone games were implemented in Botswana, Kenya, Malawi, Mozambique, Tanzania, and Uganda with over 6 million handsets in total. These games were designed to help educate participants on HIV/AIDS prevention, healthy living for those infected with HIV, and how to fight stigma and discrimination surrounding the disease. In some countries like Uganda, considerable impact of the project on behavioral changes particularly among the youth was registered (Crown Agents 2014). The Mobile Midwife project currently running in Ghana aims to improve antenatal and neonatal care among the rural poor. It sends text and voicemail messages to women during their pregnancies, particularly messages on postpartum depression or postpartum anxiety and messages on essential vaccinations and management of critical childhood diseases. In the first 2 years after the program was launched in 2010, more than 20,000 users had enrolled (Cheers 2013). "Learning about Living" is a collaborative pilot program in Nigeria and provides a forum for young Nigerians to be educated on health-related issues such as sex, AIDS, personal development, relationships, and healthy living skills. With "My Question" option, the youth can get to know about healthy living by sending a text message, calling a toll-free line, or sending an e-mail. When the project was launched in 2007, it was piloted in three places in Nigeria. The project saw an early success in that the service received close to 2500 health-related questions in the first 5 days and about 10,000 questions within the first month after its launch (Vital Wave Consulting 2009). The use of SMS or email-based interventions to change behavior has also been piloted in several other sub-Saharan African countries such as Democratic Republic of the Congo, Ghana, Kenya, Nigeria, South Africa, Uganda, and Tanzania, and generally, some encouraging results have been registered (Gurman et al. 2012; Corker 2010).

14.4.4 Surveillance

One of the challenges that health systems in sub-Saharan African countries still face, and will continue to face if not checked, is the inadequate capacity to carry out effective disease surveillance and infectious disease outbreak investigation (USAID/Ghana 2013). Brinkel et al. (2014) agree and observe that health surveillance as well as disease monitoring in the region is still weak. It is characterized by very high costs. These high costs range from logistical, financial to infrastructural provisions. However, the use of mobile technologies has reduced the costs of disease surveillance and monitoring to a greater extent and has provided a more effective means to perform surveillance in some sub-Saharan African countries. Kahn et al. (2010) concur and state that mHealth has the capacity to deliver lifesaving information even to the most distant, remote, and resource-poor areas in developing countries. It is important to note that early access to disease reports by health professionals can lead to a fast and timely identification and control of disease outbreaks (Kahn et al. 2010).

For example, the malaria surveillance study in Botswana applies an immediate case-based notice per confirmed positive malaria case and offers supplementary weekly information. This enables rapid response toward the spread of malaria in a particular area (Chihanga et al. 2012). Similarly, community-based longitudinal demographic surveillance sites (DSS) exist in 12 sub-Saharan African nations, and the system collects NCD data on births and mortality by verbal autopsy. The DSS has provided important information on changes in the major causes of mortality (Steyn et al. 2005; Tollman et al. 2008). For example, data from one DSS cohort in South Africa discovered that four of the top five most common causes of death in adults are noncommunicable conditions (Steyn et al. 2005). In Uganda, an AED SATELLITE program used for disease surveillance and used wireless-enabled PDAs for health data collection and reporting produced a 24% cost saving on surveillance compared to the traditional paper approach. Eighty-seven percent of the health professionals engaged in the program acknowledged that the system allowed them to make faster and more accurate diagnoses and response to an outbreak (Berhane 2008). In Mozambique, PDAs and other GPS devices were also deployed for malaria monitoring project. The mobile technology system was meant to enable health professionals implementing malaria programs to make quick and accurate decisions. The health professionals use the PDA and GPS devices to gather data and transmit it via the GPRS network to a central database used to produce health information, which helps the Mozambican government to effectively allocate resources (Vital Wave Consulting 2009). The Ministry of Health in Malawi in partnership with John Snow Inc., a public health consulting firm, has created cStock that used an SMS-based system that enables health workers to monitor and track the number of drugs at local clinics, reducing the chances of drug deficiencies (Cheers 2013).

14.4.5 Management

In sub-Saharan Africa, the health management systems that address health service challenges are constrained both in terms of resources and capacity (Vital Wave Consulting 2009). It has been reported that weak health information management systems (HIMS) posed a critical challenge to reaching the health-related Millennium Development Goals in sub-Saharan Africa. Sub-Saharan Africa continues to grapple with a huge problem of poor health data collection, analysis, and management (WHO 2013; Kumar 2007). Health data storage, management, and analysis require robust information management systems (Sheikh 2014). There is an urgent need to find ways to strengthen HIMS in this part of the world. In other words, a well-functioning HIMS should produce accurate, dependable, and timely data on health status, health determinants, and health system performance and be capable of analyzing this information to guide health activities and decision-making processes across all other health system building blocks (Vital Wave Consulting 2009). There are some concerted efforts being undertaken in some sub-Saharan countries to strengthen existing HIMS. Some sub-Saharan countries have registered benefits from their well-functioning HIMS. Studies conducted in some African countries that have a well-functioning HIMS found out that the average patient visits to a health facility in these countries were 22% shorter compared to other countries, with the time spent consulting or attending to the patient reduced by 58% and patients spending 38% less time waiting in the clinic (Rotich et al. 2003). Similar studies also show improvements in the accuracy of clinical information, prescriptions, and lab tests, easy program monitoring, improved management of chronic diseases, and timely and helpful reminders and alerts about lab results and medications (Douglas et al. 2003; Anokwa et al. 2012). An example of where the use of HIMS scored success was in Tanzania. When the Tanzanian government introduced the integrated management of childhood illness (IMCI), it did not show any signs of successes. This is because there was inadequate supervision, inadequate training of health works, and a slow implementation process that had significantly weakened its likely impact. However, there were efforts to address some of these problems by the project's research team. In an attempt to address these problems, the team created a program called e-IMCI which ran on a PDA device. The program provides a step-by-step guide on how to enter, retrieve, and disseminate vital information. Although long-term studies on the effects of e-IMCI are required, preliminary results from the pilot implementation were significantly encouraging (Dimagi 2015).

14.4.6 Compliance

One area that sub-Saharan Africa has been praised for is compliance to treatment. A 2015 report published by Unite for Sight (2015), an international health agency, stated that claims that compliance challenges are overwhelming in developing countries are not grounded in evidence. In fact, according to the report, adherence rates in sub-Saharan African countries are either equal or higher than adherence rates in developed countries. For example, HIV patients in Africa achieve close to 90% adherence rates significantly exceeding those achieved in a developed country like the USA or Canada (Unite for Sight 2015). This is remarkable, given the enormous obstacles in the health sectors in these poor regions of the world. However, there is evidence that shows an overall high proportion of patients defaulting tuberculosis (TB) treatment in sub-Saharan Africa. Four out of the five studies reported the percentage of default above 20% (Castelnuovo 2010). Poor compliance and patients defaulting on anti-TB treatment can lead to a significant increase in multidrug-resistant mycobacteria in the continent (Castelnuovo 2010). On the other hand, a study showed that on average, 17.6% of hospital admissions in 2008 resulted in readmissions within 30 days of discharge, 11.5% within 15 days, and 6.2% within 7 days due to noncompliance. Whereas variation in readmission rates varies by hospitals and geographic regions, reducing hospital readmissions could lower healthcare costs (Roney 2012). Research on effective ways to overcome noncompliance is underway, and the use of mobile technology to improve compliance tops the list. When using mobile technologies in treatment compliance, it is described as the sending reminder messages, by voice or SMS, to patients with the aim of achieving treatment compliance, disease eradication, and overcoming challenges such as drug resistance. In many cases, SMS has been deployed to support patients with conditions such as diabetes, HIV/AIDS, and TB (WHO 2013). This explains why sub-Saharan African population compliance rate is very high even more than in the USA or Canada. Mobile and wireless technologies offer hospitals a mean to lower medication noncompliance, which has been proven to be one of the biggest factors in high hospital readmissions. Mobile technology can help patients to stick to medication orders given by a health professional. It can inform patients on the usefulness of medical adherence, especially prescription adherence (Roney 2012). There are a number of cases where the use of mobile technology in medical compliance has improved adherence. For example, before a mobile device known as "SIMpill," which monitors and reminds the patient to take medication as prescribed in real time, was introduced to help improve patient compliance in South Africa, there was a 22–60% patient adherence rate. However, with the introduction of SIMpill in a pilot project, it showed that patient compliance could jump to over 90% (Vital Wave Consulting 2009). SMS reminders sent to patients have improved appointment adherence in Malawi (Mahmud et al. 2010) and follow-up in Nigeria (Odigie et al. 2012) and in Cameroons (Davey et al. 2012). SMS sent for treatment compliance with or without the use of smart pill boxes has been reported in Uganda (Siedner et al. 2012).

However, despite all the opportunities provided by mHealth solutions, there are challenges encountered during mHealth implementation. In the next section, this chapter discusses the challenges that mHealth initiatives in sub-Saharan Africa are facing.

14.5 Challenges of mHealth in Sub-Saharan Africa

Although a lot has been written on the potential benefits of mHealth in sub-Saharan Africa, its uptake has been limited compared to other parts of the world (Mars 2013). The uptake of mHealth in sub-Saharan Africa has been faced with a number of challenges, and among these challenges is a shortage of ICT trained doctors and nurses who can effectively use the mHealth system. The unfortunate reality again is that most mHealth systems involve a lot of steps, adding extra steps into the routine clinical workflow. This normally becomes a huge burden to the already overworked doctors and nurses (Mars 2013). Studies have shown the existence of technical challenges stemming from the lack of competencies in mobile-based applications usage on the part of the health professionals (Pascoe et al. 2012). Besides the challenge of ICT illiterate medical practitioners, a large population of people in many sub-Saharan African countries are illiterate and are digitally backward. Web-based solutions for patient-centric healthcare are currently largely irrelevant because, in poor communities, people are mostly ICT illiterate and just a few of the over 2000 African languages are available on the Web (Mars 2013).

Besides digital backwardness, other reported challenges affecting the implementation of mobile phone-based health services in sub-Saharan Africa are technical, financial, and infrastructural challenges, data security, as well as challenges concerning the accuracy of mHealth medical diagnosis tools (Brinkel et al. 2014). As far as infrastructural challenges are concerned, Internet penetration in Africa is half that of Asia and the Pacific and the lowest of any developing world region. In rural areas where mHealth services are much needed by the poorest of the poor, it is least likely to be provided because of inadequate infrastructure and high connectivity costs (Mars 2013). In fact, a study carried out by Kaplan in 2006 argued that mobile technology may not be an effective tool for healthcare interventions for two primary reasons: lack of access to these mobile technologies by many people and limited evaluations of effectiveness. However, this was way back in 2006 when mobile and wireless technology penetration in sub-Saharan Africa had not yet gained the momentum as it has now. A more advanced mobile health initiatives require a high level of ICT literate population and medical practitioners and significant infrastructural establishments such as state-of-the-art telecommunication infrastructure, like the 3G and 4G networks (WHO 2011). Crul (2014) observes that modern telecommunication infrastructure is being deployed across the world, driven in particular by strong consumer demand for technology-based services and also the enactment of good ICT policies to stimulate growth in ICT infrastructure and network connectively.

Although a lot of research and pilots projects have already been implemented, mHealth's practical application is still largely undeveloped. Projects are often not sustainable enough to go beyond the pilot phase. Scaling up implementation is often limited because a global, consistent framework including indicators and evaluation methods is still lacking (Crul 2014). Whereas a general acceptance of mHealth at the community level in many sub-Saharan countries was reported to be good (Brinkel et al. 2014), a number of cases were reported where physicians and nurses resist mHealth technologies. Many physicians and nurses were slow in adopting the new technologies, along with the "fee-for-service" mind-set. If the health authorities do not check this, it could act as a dampener for the rapid adoption of mHealth. For example, for some reasons, nurses refused to use the mobile-based solution to record stock used for patients in a large private hospital (Whittaker et al. 2011). In another case, health professionals who were given mobile phones to report on patients who were on treatment for drug-resistant tuberculosis completed less than a third of reports (Chaiyachati et al. 2013). Government policy can be an important first step toward mass physician acceptance (Vishwanath et al. 2012). Vishwanath et al. (2012) observe that in order for health professionals to accept to use mobile technology services, government action and commitment coupled with efforts from other stakeholders are crucial. Government policy will act as a foundation for pushing for health professionals to use mHealth solutions, and once they attain comfort levels, it will be easier to integrate other mobile technologies into healthcare delivery.

Many sub-Saharan countries do not have enough legislation to foster mHealth. Regulators across the world must carefully address issues that can restrain the growth of mobile health. Regulations should adequately address issues such as certification of devices as well as applications and standardization of procedure and systems (Vishwanath et al. 2012). Malaysia, for example, took bold steps way back in 1996, declaring various telehealth-related laws and implementing a “Multi-Media Super Corridor” initiative and introducing a Lifetime Health Plan with a “lifelong Personal Health Record (PHR)” (Scott and Mars 2014).

14.6 Conclusion

Despite bearing about 71% of the global distribution of communicable diseases (infectious diseases), sub-Saharan Africa still grapples with the weakest healthcare system, shortage of well-educated healthcare professionals, inadequate infrastructures, and laws for national and international funding toward the health sector. A very large section of the population in sub-Saharan Africa has very limited or no access to healthcare clinics and basic healthcare services. There is evidence that solutions have been developed for this life-threatening problem and save the lives of millions. Limited progress has been made to this date. Since this is a complex problem, the world has been unable to realize real success. However, many scholars and health practitioners believe that the use of mobile and wireless technology is an appropriate response to such dire circumstances. They believe that mHealth can strengthen and improve the current healthcare system, and it has the potential to deliver healthcare to patients in the most remote areas. Despite the numerous challenges associated with mHealth implementation and adoption, there is an overwhelming evidence that mHealth has improved health services in the form of prevention, surveillance, management, and compliance in sub-Saharan Africa. An integrated approach and close cooperation among different stakeholders are critical to move toward scaled and sustainable solutions.

Appendix

Group	References
Introduction	IPIN (2012), WHO (2016), Soucat (2014), WHO (2012), Vishwanath et al. (2012), WHO (2011), Kahn et al. (2010), Crul (2014), Ogunmefun et al. (2010), Seebregts et al. (2009), Skinner et al. (2007), Tomlinson et al. (2009), Unite for Sight (2015)
Methodology	Hemingway and Brereton (2009), DFID (2013), Kowalczyk and Truluck (2013), Zanker and Mallett (2013), Kahn et al. (2010)
mHealth in SSA	Vishwanath et al. (2012), Crown Agents (2014)
Mobile Tech in SSA	Brinkel et al. (2014), Piette et al. (2012), Vishwanath et al. (2012), UCC (2015), Lallana (2007), Aker and Mbiti (2010)

Group	References
Prevention	WHO (2013), Unite for Sight (2015), Gaziano et al. (2007), Crown Agents (2014), Soucat (2014), Vital Wave Consulting (2009), Cheers (2013), Abegunde et al. (2007), Wakefield et al. (2010), Odigie et al. (2012), Silva et al. (2015), Gurman et al. (2012), Corker (2010)
Surveillance	Berhane (2008), Chihanga et al. (2012), Steyn et al. (2005), Vital Wave Consulting (2009), Cheers (2013), ITU (2013), USAID/Ghana (2013), Brinkel et al. (2014), Kahn et al. (2010), Tollman et al. (2008)
Management	Douglas et al. (2003), Dimagi (2015), Rotich et al. (2003), Vital Wave Consulting (2009), WHO (2013), Kumar (2007), Sheikh (2014), Anokwa et al. (2012)
Compliance	Vital Wave Consulting (2009), Mahmud et al. (2010), Odigie et al. (2012), Siedner et al. (2012), Skinner et al. (2007), Unite for Sight (2015), Roney (2012), WHO (2013), Davey et al. (2012)
Challenges of mHealth in SSA	Mars (2013), Pascoe et al. (2012), Brinkel et al. (2014), WHO (2011), Crul (2014), Vishwanath et al. (2012), Whittaker et al. (2011), Chaiyachati et al. (2013), Sheikh (2014)

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Chapter 15
Big Data in mHealth

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15.1 Introduction

The generated health-related data have grown exponentially in the past decades with the availability of cheaper, smaller, and wireless enabled mobile technologies including smartphones, tablets, and wearables. The significant amount of data generated by a diverse and large number of mobile health sources is not only so voluminous but also fast and complex to be processed and stored by traditional methods. Furthermore, these data usually do not have a common structure. Its uncertainty and reliability are also important issues which need to be considered in mHealth applications. While the use of such data offers significant benefits for individuals, its analysis in an aggregate form at different stages has potential to provide unprecedented use and value for a diverse set of stakeholders. Essentially, all these characteristics of mHealth data map to 5Vs of big data, which are volume, variety, velocity, veracity, and value. Due to these characteristics, mHealth data can essentially be considered as big data. Hence, the utilization of big data approaches in the mHealth domain has potential to provide promising solutions to lower the healthcare costs for governments and improve diagnostic and treatment methods for individuals and populations health. As discussed in Sect. 15.2, the widespread adoption of big data approaches in the mHealth domain enables us to devise applications. At the individual level, it is possible to learn more about individuals beyond their clinical visits. At the community level, it is possible to detect diseases at an early stage and discover new treatment and diagnosis methods. At the regional level, it is possible to improve the productivity and efficiency in healthcare services, thereby lowering healthcare costs.

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E. Sezgin et al. (eds.), *Current and Emerging mHealth Technologies*,
https://doi.org/10.1007/978-3-319-73135-3_15

Although there is a potential for substantially enhancing healthcare services using big data technologies, there are various social and technical challenges as discussed in Sect. 15.3. The social challenges do not only include the acceptance and adoption of mHealth technologies by individuals and healthcare practitioners but also pay attention to issues related to privacy and ethics. The lack of common data standards in mHealth applications, security issues, and governance and policy issues are the most remarkable technical challenges.

The inherent characteristics of the domain must also be taken into account when choosing appropriate big data tools and techniques for mHealth applications. For example, stream processing approach is the most suitable when there is a need to respond to certain events immediately. On the other hand, batch processing is much more applicable for working with aggregate data to extract valuable information. The identification and inference of certain events such as detection of unexpected occurrences for the timely reaction may require incorporation of complex event processing into big data platforms. Besides, health data processing necessitates interdisciplinary collaboration of healthcare practitioners, data scientists, and IT specialists. On this basis, a framework is proposed in Sect. 15.4 to facilitate big data adoption in the mHealth domain. The framework abstracts away practitioners working with health data from technical intricacies of processing environments. Hence, mHealth application development and deployment process in big data platforms can be simplified substantially.

15.2 Big Data Analytics in mHealth

mHealth empowers patients with self-assessment and allows them to monitor their health conditions frequently and independently of healthcare practitioners. Furthermore, mHealth enables healthcare practitioners to treat patients more effectively by using remote monitoring and consultation, instant access to medical information of patients, and online prescription services. The widespread use of mobile devices makes the collection of health-related data from numerous types of sources possible. Mobile phones/smartphones and their applications, mobile biomedical sensors, remote patient monitoring products, social media, and electronic health records are among such sources that can be used for this purpose. Moreover, the collected data can be turned into meaningful and valuable inputs to personalized diagnostic and treatment models.

Smartphones by far are the most commonly used mobile devices in our daily life and can be considered as one of the most prominent platforms for mHealth applications. Today, the mobile applications that track personal data such as the number of steps taken daily and daily calorie intake are immensely popular among people. According to the Pew Internet and American Life Project (Anderson and Rainie 2012), 82% of American adults have a cell phone, nearly three out of ten Americans have accessed medical information using them, and about 10% of the population have applications on their phones that help them to manage their health conditions.

Health-related smartphone applications are categorized by Balandin et al. (2013) as general healthcare and fitness, medical information, remote monitoring, collaboration and consultation, and healthcare management. There are also disease-specific applications for mental health, diabetes, Alzheimer, and Parkinson.

There are also mobile medical devices that are specifically designed to monitor heart rate, blood pressure, and glucose level as well as to track sleep patterns and even brain activity. Thus, healthcare providers can keep patients under continuous observation and detect the symptoms at an early stage to treat them much more effectively. Moreover, the Internet of Things (IoT) concept offers a pervasive health environment by the interconnection of various mobile devices. Such a pervasive environment makes it possible to monitor and analyze health-related data at the personal and population levels in order to produce extended benefits.

The changes in diagnostics and treatment approaches and many of the health-related decisions are being driven by data analytics. The health domain historically generates a large amount of data in the form of genes, medical images, electronic health records, clinical notes, and epidemiologic data, which are utilized to improve treatments and diagnostic models. The transition from such traditional data to big data begins with the emerging technological advancements in mobile technologies which have enabled us to collect health-related data from a diverse set of sources. Big data is a collection of large, complex, and continuous data from a large number of usually disparate data sources, and it is difficult to process this data by using traditional database management tools or conventional data processing approaches (Mayer-Schönberger and Cukier 2013). While the number of data sources is increasing, the heterogeneous nature, collection and processing speed, and reliability and uncertainty of collected data further complicate the extraction of information from such data. Thus, mHealth data have turned into big data.

There are five unique characteristics of big data that distinguish it from ordinary data: volume, velocity, variety, veracity, and value (Mayer-Schönberger and Cukier 2013). Volume refers to the size of data, which is the most important characteristic of the big data. The health domain has already the expansive amount of data which is generated and aggregated continuously. Velocity refers to the speed of the data which needs to be processed in a real-time fashion in most situations. In the health domain, excessive delays are usually not acceptable since every second is crucial for saving lives. Variety refers to the distinct types of data. Since the mHealth domain should bring together a diverse set of mobile devices and these data sources may generate data in heterogeneous formats, variety is an important issue. Veracity is related to the quality of the collected data (Raghupathi and Raghupathi 2014). Mobile devices operating in an uncontrolled environment may not be as reliable as devices used in a clinic. Consequently, if no special care is taken, the decisions made based on analytics carried on imprecise or inaccurate data may lead to catastrophic consequences, especially in the mHealth domain. Finally, the value attribute of the big data is the most important characteristic as it reflects the benefits of big data analytics in this domain.

Big data technologies require distinct processing methods to handle different characteristics of big data. Although applications that process big data vary within themselves, there are two notable processing methods: batch processing and stream processing. Batch processing can be defined as applying a series of operations to data, which is stored in batches, at certain time intervals (Ghemawat et al. 2003). For example, aggregate data in medical studies can be mined to detect patterns, to learn more about diseases, and to improve therapies and drugs for treatment. On the other hand, stream processing is applying operations on continuous streams of data in real time, and it provides a solution to the velocity dimension of data. Instead of being stored in permanent devices, data either flows to a processing application or is stored on temporary memory units (Osman et al. 2013). Stream processing is more suitable when the immediate reaction is critical. The continuous streams of data from mHealth devices can be analyzed using stream processing methods to detect anomalies in a patient's vital parameters in real time.

There are many use cases where big data can offer significant opportunities in the mHealth domain. Olla and Shimskey (2015) divide the mHealth use cases into eight main categories: point-of-care diagnostics, wellness, patient monitoring, compliance, behavior modification, education and reference, efficiency and productivity, and environmental monitoring. The relationship and the potential impact of big data for these use cases can be highlighted as follows:

The Point-of-Care Diagnostics Tests such as blood glucose, cholesterol, and urine level measurements can be carried out in an ambulance, at home, or in a hospital by using mobile medical devices in order to get immediate results and to offer rapid treatment to the patient. According to a study by King et al. (2016), the analysis of point-of-care diagnostics data by applying big data methods provides an important potential for enabling precision medicine or personalized management.

Wellness The applications in wellness category promote healthy user behaviors such as dieting and exercise. Although they are not intended to diagnose, prevent, or treat any disease directly, the data collected from wearable devices and other connected wellness devices can be used to improve individual patient outcomes, diagnostic procedures, and treatment methods. The mobile application named MyFitnessPal[1], which plans diets and counts calorie intake of users, utilizes big data approaches to carry out advanced analyses on the collected data[2].

Patient Monitoring Real-time data from a patient's mobile device can be monitored to detect notable changes in vital parameters. A recent study proposes a learning scheme for patients' activity recognition, in which patients only need to carry an ordinary smartphone that contains common motion sensors (Guo et al. 2016). Another study presents a big data solution for continuous monitoring of the elderly, alerting relevant caregivers when necessary, and forwarding pertinent information to a big data system for analyses (Jiang et al. 2014).

[1] https://www.myfitnesspal.com

[2] http://go.databricks.com/case-studies/myfitnesspal

Compliance A patient can be monitored to check if the prescribed medication or healthcare plan is followed accurately. This includes self-testing by using mobile biomedical devices such as pedometers, glucose meters, blood pressure monitors, and personal exercise trainers. In order to reduce the impact of noncompliance on patients, the patient compliance records can be analyzed by using big data analytics tools.

Behavior Modification Patient health records are valuable resources for making changes in daily behaviors as well as providing personalized treatment and diagnostic models. For example, Chen et al. (2016) suggest using big data analytics to classify the prognostic factors of cancer. Quan Do et al. (2015) propose applying big data methods on data collected from a mobile application in order to track personal asthma triggers, predict asthma attacks, support asthma self-management, and communicate with healthcare providers. Another study leverages a big data-driven approach for personalized care and demonstrates its applicability (Chawla and Davis 2013).

Education and Reference mHealth applications may provide up-to-date information that can be used to educate patients and healthcare practitioners (Lateef 2016). The utilization of big data in medical education can provide an outlook and insights related to the medical curriculum. Moreover, students and practitioners can access big data sets for a wide variety of research studies and projects.

Efficiency and Productivity With the help of big data applications in healthcare, physicians can access detailed information regarding patients' previous treatments, medications, and any other medical history. Being able to access such information in a fast and reliable way can improve the diagnosis processes. Therefore, this will not only reduce the cost of diagnosis by decreasing the time required to diagnose patients but also make the process more efficient. These benefits are significant at the community and institution levels. That is, the capability of visualizing patients' medical test results, writing and editing prescriptions using mobile technologies, scheduling inspection activities, and detecting epidemic diseases early, combined with big data processing applications, will provide efficiency and productivity benefits to physicians, patients, and community.

Environmental Monitoring Flu or other epidemic diseases can be scrutinized in an area by analyzing web and social media sources like Twitter, Facebook, and blogs. A recent study proposes a prototype application to collect and analyze influenza cases across different geographic locations with real-time tweet streams (Wang et al. 2016). Another study uses search queries to detect influenza epidemics in areas with a large population of web search users (Ginsberg et al. 2009). Similarly, Google aggregates their search queries to operate a web service Google Flu Trend[3] to predict flu in 25 different countries.

[3] https://www.google.org/flutrends

15.3 Opportunities and Challenges

The utilization of big data approaches in the mHealth domain creates opportunities, while it also presents social and economic implications for multiple stakeholders, each of which has different interests. Patients or individual members of the population can improve their lifestyle and wellness. Disease avoidance is a prominent concern for our everyday lives. If available, healthcare providers can utilize stream processing-based big data approaches to handle emergencies better and faster or get prompt recommendations in life-threatening conditions. On the other hand, batch processing-based big data approaches can be used by care providers to monitor chronic conditions by analyzing data in an aggregate form remotely. Furthermore, medical data turned into valuable information using batch processing can enhance medical research carried out by healthcare providers and pharmaceutical companies. On the other hand, Internet-based companies are at an advantage since advancements in big data domain occur according to their interests, and they are already more familiar with the domain compared to any other stakeholder. Moreover, they tend to accumulate large sets of data as people use their products or services, and some of these data fall under the category of mHealth data. Together with healthcare providers, Internet-based companies are in a good position to develop data mining and machine learning techniques to generate disease surveillance algorithms. Since governments are interested in tracking compliance of entities with health regulations, they can do food safety monitoring or air quality analysis in a particular area to efficiently detect and penalize illegal activities. Not only governments but also health insurance agencies can use big data approaches to analyze health risks for individuals better, and through measures like preventative care, costs associated with healthcare can be reduced.

15.3.1 Opportunities

The intersection of big data and mobile healthcare technologies presents opportunities at multiple levels including the individual, community, and regional levels (Kahn et al. 2010). At the individual level, there are healthcare monitors which can transmit a variety of data such as heart rate and blood pressure in real time, and such data can be stored in batches which contribute to big data. Ubiquitous lifestyle applications available in smartphones today also collect data from users. Mobile healthcare data collected from a particular group of individuals (such as children with type II diabetes living in Ohio) elevates the issue to the community level. With the increase in volume and variety, data becomes more valuable for medical research. As we move on to the regional level, data is collected at a larger scale. Hence, it is possible to utilize additional mobile sensor-based technologies at different geographic locations, for instance, to continuously monitor air or water quality for the welfare of the society.

15.3.1.1 Opportunities at the Individual Level

Recent research attempts to apply recommendation techniques to healthcare, where a health professional or a patient becomes the beneficiary of such systems (Huang et al. 2015). From an individual perspective, utilization of big data technologies may offer significant opportunities. For instance, a patient-oriented decision support system can deliver relevant and high-quality medical information available on the Internet and spare the patient information overload, based on long-term medical history as well as current medical conditions (Wiesner and Pfeifer 2014). The system can also recommend a list of medical experts which is related to the patient's medical condition (Hoens et al. 2013). In an expert-oriented context, a clinical recommendation system can assist medical decisions as part of handling emergency cases where there is little advance information available. Healthcare professionals can get assistance by giving the current condition as an input to the system containing the medical history of the patient. Mobile technologies support such systems by making information available anytime and anywhere (Varshney 2014). mHealth devices can also provide additional context related to individuals in the form of sleep patterns, logs from heart rate monitor, and results from daily questionnaires.

Preventative care can be augmented by big data in the mHealth domain through the use of wearable monitoring systems, smartphone-based applications, and the Internet-connected exercise machines (Varshney 2014). Big data gathered from these sources can be further analyzed to identify individuals in early stages of some diseases or those who should change their lifestyles to avoid a certain health problem. These patients would need proactive care in addition to preventative care (Cyganek et al. 2016). Another research focuses on recognizing emotional states of users through mobile phone sensor usage and reacting to emotional states by serving up personalized content (Mousannif and Khalil 2014). This research attempts to model emotions by extracting valuable data obtained from mobile devices such as facial photography, speech, and text.

The treatment or management of chronic diseases such as diabetes, cancer, or heart diseases may require continuous care by a health professional in addition to continuous medication, training, and a special diet. If all of these requirements are not met completely, which might be the case for individuals living in rural areas as well as low-income individuals in developing countries, health systems may provide self-care support for patients (Kahn et al. 2010). Big data produced by a multitude of mHealth devices, including ubiquitous smartphones used by patients, can be stored in medical databases to enable remote care by health professionals. If such data is streamed to a complex event processing system, certain risks can be discovered early, and thus life-saving notifications can be sent to relevant care providers in real time.

15.3.1.2 Opportunities at the Community Level

Big data collected from mHealth applications which are used by individuals may also provide opportunities at the community scale. Such data is already being collected from individuals by Internet-based companies. For instance, Google's Flu Trends applies machine learning techniques to search queries in order to detect influenza outbreaks (Huang et al. 2015). This is a preeminent example of stream analytics which is utilized for real-time epidemic surveillance in healthcare. Data streamed from mobile health technologies can be processed in real time as well to make more accurate predictions. On the other hand, stored mHealth data is also a valuable resource that can be used for batch analysis to enhance medical research about diseases, therapies, and drugs (Mousannif and Khalil 2014). Furthermore, this data can be clustered according to specific patient attributes like disease (e.g., diabetes, cancer), demographics (e.g., age, gender), or context gathered from mHealth devices (e.g., geographical area) to carry out more specific analyses.

15.3.1.3 Opportunities at the Regional Level

Regarding the regional level, big data coming from a larger population is valuable for a variety of stakeholders. Augmented by mobile technologies, preventative care and proactive care aim to improve the well-being of individuals by decreasing the need for treatment and medication. Self-care extends physical boundaries for continuous monitoring by a healthcare professional so that not all patients with a chronic disease need to stay in hospitals. Small improvements from such activities can cut down healthcare costs for governments and insurance agencies at a greater scale. In addition, insurance agencies can apply machine learning methods on healthcare data logs to better assess risks and forecast their cost structures. Therefore, this approach may ultimately lead to more efficient pricing strategies.

At the regional level, additional sensor-based technologies can be utilized for real-time safety monitoring purposes (Huang et al. 2015). For food safety monitoring, Baidu produces smart chopsticks[4] which measure various properties of food. To infer air and water quality in a particular region, sensors can be deployed to selected locations. A complex event processing platform can take real-time data from such IoT sources and analyze them together with the data coming from mHealth devices and social media posts. Hence, certain patterns and events can be identified, and an alarm is triggered if needed. This is also valuable for governments in terms of enforcing regulations more quickly and effectively.

[4] http://blogs.wsj.com/chinarealtime/2014/09/03/is-y

15.3.2 Challenges

Before these opportunities materialize, there is a need to address various social and technical challenges. The acceptance of mHealth applications and devices by patients in their everyday lives is directly associated with immediate benefits they provide. The adoption and proper use of these technologies by medical personnel is also another factor. The development of big data applications to serve specific goals requires broad expertise. Training the medical staff, hiring a skilled workforce, and acquiring the necessary hardware and software increase costs. Privacy is always an important consideration when discussing big data analytics. With respect to technical challenges, data generated by many mHealth applications and devices are unstandardized and unstructured. Therefore, data must be preprocessed before being used. This is usually a complex and time-consuming task affecting the overall accuracy and the efficiency of the analysis, which may determine whether a patient stays alive or dies. Last but not the least, the proper presentation of analysis results is very important for the stakeholders who may lack necessary technical background.

15.3.2.1 Social Challenges

There is a multitude of heterogeneous smart applications and IoT devices/sensors which can generate mHealth data. Whether this data can be considered as “big data” is mostly determined by the level of acceptance of mHealth technologies by the society. If individuals do not use mHealth technologies sufficiently, the limited amount of data can lower its quality which in turn diminishes the overall value generated. If acceptance stays confined to some regions or groups, analysis results may not be generalized to the entire population. Likewise, technology adoption by healthcare professionals has the same effect. A research study investigated human drives on the adoption of mobile information communication technologies in patient care settings by attempting to understand how nurses utilize mobile technologies as part of their work (Junglas et al. 2009). Results showed that the use of mobile technologies was influenced by a number of unintended use cases, like using the system on another nurse’s behalf or using the system at another location or time. Such cases may prevent analysis techniques from capturing important context information. In a worse scenario, wrong context information may act as corruptive input to important decision-making processes.

Healthcare professionals should collaborate with big data experts in order to develop the right tools and techniques. The development and utilization of data mining, machine learning, and data analytics applications require high-level expertise and extensive training. Therefore, it is costly to hire a workforce of data scientists to work in the mobile healthcare domain or to train medical staff to utilize advanced analysis techniques. Moreover, regardless of being hosted in a public or private cloud, the deployment of data analytics applications incurs significant infrastructure costs. Hence, convincing medical authorities to make the buy decision may not be easy (Asri et al. 2015). On the other hand, the cost of wireless mobile healthcare technologies can be subsidized partially or fully by governments or health insurance agencies to give patients an incentive to use them.

Privacy is an important challenge when developing any big data platform. In the discussion of opportunities, it is recommended to log every possible data for batch analysis purposes. However, data storage agreements and conditions are usually traded off in exchange for benefits while collecting and using data in mHealth applications. It is claimed that patients would be open to share information for greater benefit (Asri et al. 2015). However, individual and communal health data can be pretty sensitive. There are many Internet-based companies providing healthcare products or services, and patients are expected to depend on companies' security and privacy policies. Nevertheless, there is always a risk that confidentiality may be compromised, resulting in undesired exposure of personal health information.

15.3.2.2 Technical Challenges

In the healthcare domain, having accurate and precise information in a timely manner is essential. In this regard, there are difficulties associated with big data processing and the use of available mobile devices. Healthcare data generated by smart applications, smart devices, and IoT sensors have heterogeneous nature. Hence, no common format that applies to all can be assumed. This issue needs to be addressed as part of preprocessing steps before further analyses. The data collected from different regions, or even from different parts of the same region, may not have a standard format, and different organizations may store the data in different formats. Therefore, in order to simplify analyses on aggregate data, homogeneous information may be stored in a common data warehouse (Asri et al. 2015).

In addition to the quality of data, the efficiency of analyses contributes significantly to the value produced especially when information extracted is useful only for a limited amount of time. In such cases where real-time outputs are necessary, there is a trade-off between preprocessing time and variations and errors in the results. At the individual level, incorrect, partial, or misunderstood information may mislead patients and cause confusions or create a false sense of security. At the community level, such information may cause mismanagement of disease outbreaks, false alarms, and panic (Kahn et al. 2010).

Valuable information produced after analysis should be presented to healthcare professionals or patients in a meaningful and intuitive way. Since not all stakeholders do possess knowledge or experience to comprehend outputs produced by programming languages, the graphical presentation is suitable to visualize results. While there are extensions available to some machine learning tools which provide general plot functions, these tools are difficult to learn (Huang et al. 2015). Other visualization software may not accept all data formats, may be time-consuming to use, or may require wrappers or interfaces to be used with processing tools.

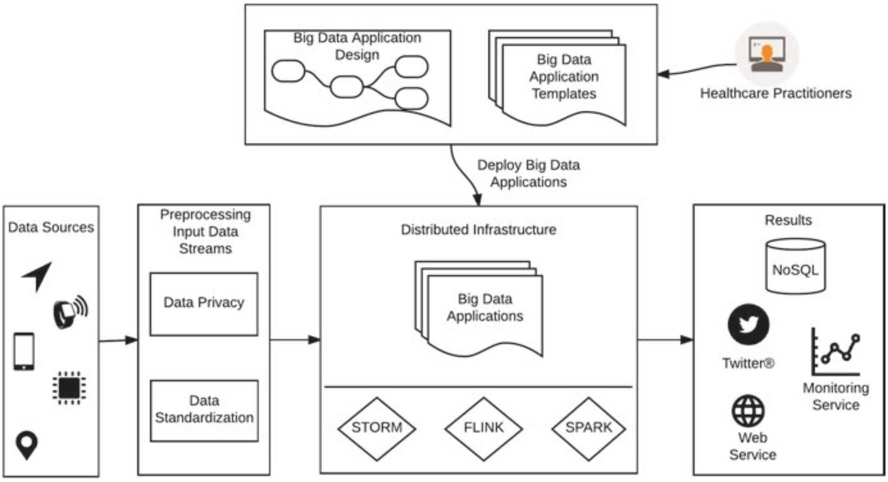

Fig. 15.1 The proposed framework architecture

15.4 Architectural Framework

With the help of the mobile devices which continuously produce large amounts of structured and unstructured data, big data analytics has a potential to enable us to improve healthcare services and maximize knowledge and insights in the healthcare domain. However, healthcare practitioners, businesses, and governments face with difficulties in managing and utilizing these data due to the social and technical challenges highlighted in Sect. 15.3, which may hinder the adoption of big data technologies in the mHealth domain. Hence, we propose a framework to abstract healthcare practitioners away from the technical complexities to accelerate the adoption process. The proposed framework aims to facilitate the development and deployment of big data applications by health practitioners.

As depicted in Fig. 15.1, the proposed architecture consists of five main components: big data application design, big data application templates, preprocessing input data streams, distributed infrastructure, and distribution of the results.

Health data has domain-specific characteristics. Therefore, data scientists need significant expertise in healthcare domain to aggregate and process such data properly. However, neither data scientists nor IT specialists are familiar with the health domain, nor do health practitioners have the required expertise in data analytics to develop their applications. This introduces social challenges where expertise barrier hinders the adoption of big data technologies and increases the processing costs. Consequently, the most important component of the proposed framework is *big data application design*, which allows healthcare practitioners to construct big data applications visually. Data mining, machine learning, and aggregation algorithms are

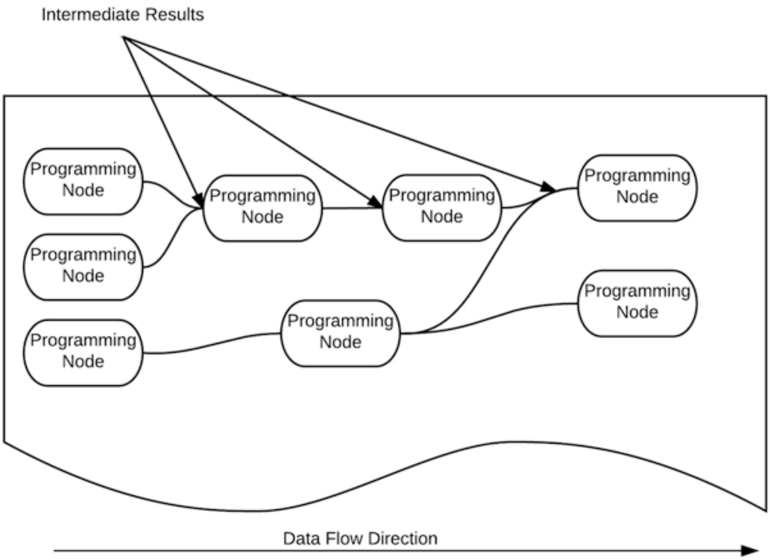

Fig. 15.2 Big data application programming model

provided as visual programming constructs. Hence, applications can be developed by drag-and-drop operations of such building blocks to form directed graphs. In these applications, vertices represent data mining, machine learning algorithms, as well as basic programming elements, while edges represent data streams which correspond to intermediate results as shown in Fig. 15.2. In order to support compatibility, the programming nodes are designed to take and produce data in a common standard form. Thus, the application logic can be built by just connecting the programming nodes without worrying about their internal details and interfaces and nodes. While there are some studies on visual programming-based data processing such as KNIME (Berthold et al. 2009), Orange (Demšar et al. 2004), Kepler (Altintas et al. 2004), and RapidMiner (Mierswa et al. 2006), these tools do not support execution in a distributed environment. Thus, they are not scalable and do not completely fit the big data use cases. Hence, a visual programming language and the relevant toolset customized for distributed processing of mHealth data are provided within the framework.

The *big data application templates* component contains the predesigned and tested visual applications provided by some vendors to healthcare practitioners. The existing visual application templates can be customized and reused in different contexts by attaching them to data sources of interest. Thus, healthcare practitioners can select a predefined application template from the marketplace and just define the data sources and distribution channel to execute and deploy the application without any extra effort.

In this framework, a large set of *data sources* such as wearables, smartphones, and mobile biomedical sensors need to be integrated into the platform. Due to their heterogeneous nature, these data sources may generate data in disparate formats. Therefore, data variety is an important challenge that needs to be overcome. Moreover, the generated data includes the patient's private information and health records. There are also strict government governance and policies to transfer the data over the Internet. Hence, the *preprocessing input data streams* module plays a central role in our framework to convert data into a common format and protect data privacy for further processing. In this way, preprocessing module addresses social and technical challenges including privacy and quality of data. This is based on data standardization to define a common standard for receiving structured, semi-structured, and unstructured data from a various number of resources. Data privacy should be achieved via anonymization or encoding of personal data such as name, surname, and social security number.

The deployed applications require fast and scalable infrastructures to handle big data effectively. Therefore, big data platforms are established on a *distributed infrastructure* to address the technical challenges since real-time results can become a matter of life or death in many situations. User-defined applications are deployed automatically on the distributed infrastructure to handle unique characteristics of the big data. On the other hand, the requirements of big data applications vary according to use cases. For instance, a monitoring application needs to process stream data and produce results in a real-time manner. On the other hand, a predictive analytics application needs to deal with bulk data to detect potential risks about the production in upcoming weeks/months. There is no "one-size-fits-all" big data solution. Instead, each big data platform has its own advantages and disadvantages. Therefore, the proposed framework aims to support multiple big data platforms such as Storm[5] (Toshniwal et al. 2014), Spark[6], and Flink[7] (Carbone et al. 2015) (Apache). Hence, according to specific characteristics of an application under design, one of the supported platforms can be chosen. Moreover, by considering the designed application logic and use cases, the framework itself can offer a suitable big data platform on which the application will run.

The *results* of the applications may be forwarded to interested parties in different forms. Each distribution channel is defined as a programming node in the visual editor. Thus, users may select more than one distribution channel to deliver the results. In this way, for instance, certain problems about patients may be forwarded to healthcare practitioners as notifications, or the results can be delivered to external entities via web services for data visualization or monitoring purposes. Accordingly, the challenges of domain experts having seamless access to such results are properly addressed.

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[5] http://storm.apache.org

[6] http://spark.apache.org

[7] http://flink.apache.org

15.5 Conclusion

As wireless enabled mobile technologies become cheaper, smaller, and ubiquitous, they are increasingly adopted into the healthcare domain. This trend is supported with the advancements in the cloud computing domain as well as decreasing costs in storage units and processing power. There is a significant amount of data generated by mHealth devices and technologies, and there are significant opportunities if this data is properly analyzed in real time as well as in batches. Depending on the source of data and how it is analyzed, opportunities can be at the individual, community, or regional levels. These levels are not completely isolated from each other. For instance, information valuable at the individual level can be aggregated to be valuable at the community level, or vice versa.

A diverse set of devices and services generate voluminous data which is complex, unstandardized, and moving fast. Therefore, there are several technical challenges associated with these characteristics of big data in the mHealth domain. In addition to these challenges, there are also social challenges to be addressed before mHealth-related big data can be utilized appropriately. Social challenges include acceptance by society, adoption by medical professionals, integration costs, expertise barrier, and privacy.

In this chapter, we also introduce an architectural framework providing a higher-level abstraction programming model which can help to overcome sociotechnical challenges and invoke widespread user adoption. Using the proposed framework, healthcare practitioners who have the expertise and deep knowledge in the medical domain but limited programming skills and experience will be able to use big data application templates or develop their applications on a visual canvas. Hence, the user is abstracted away from the complexities of analysis algorithms and intricacies of preprocessing, standardization, and anonymization of input data collected from heterogeneous mHealth sources. For this purpose, important machine learning libraries are provided as visual programming nodes in the framework. In this context, the programmer is an iterative prototype generator who has the domain experience and knows organizational culture and bureaucracy, procedures, processes, and individuals. The programmers may have direct interaction with medical staff and patients. They can identify requirements, data sources, and valuable outputs so that the end product will be accepted by society and adopted by the medical community. The direct interaction with stakeholders and rapid development also allow iterative development as feedback from tests can be reflected into results quickly. Hence, the framework serves as a bridge between end users and the use of big data technologies in the mHealth domain. Utilization of the framework is expected to provide significant benefits in the widespread use and adoption of mHealth technologies.

The healthcare sector is associated with the significant amount of costs, inefficiencies, and controversial regulations in many developing and developed countries. Without proper healthcare, society remains unable to be productive. As a result, economy cannot grow to its full potential; it may even enter a plateau or shrink down. No matter how costly it is, governments must sustain the health sector. The propagation of mHealth technologies supported by big data analysis methods and techniques can lower health expenditures. With the known data mining and machine learning techniques being applied in the context of big data, expenditures can be better forecasted. In this particular industry, when small differences in everyday life such as improved wellness and preventative care are scaled to the community or regional levels, the increased efficiency can bring down costs at significant rates.

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Chapter 16
Adoption of Sensors in Mobile Health

Haluk Altunel

16.1 Introduction

Mobile health is an emerging area lying in the intersection of technology and health (Istepanian et al. 2006). Sensing technologies are among the basic building blocks of mobile health applications (Kumar et al. 2013).

New generation smart mobile devices are equipped with various built-in and nonmedical sensors, including cameras, accelerometers, gyroscopes, magnetometers, and barometers. These sensors allow collecting various health data. Heart rate monitoring applications based on picture frames captured by the cameras, dermatoscopy applications, and pedometer applications working with accelerometers and gyroscopes are the most common ones. Small and lightweight medical sensors, especially wearable ones such as T-shirt electrocardiograms, are capable of gathering health data and transmitting it to a smart mobile device via wireless protocols. Portable chemical sensors connected to mobile devices actualize the assessment and classification of diverse chemical and biological sources such as blood sugar level and cholesterol level. All types of nonmedical and medical sensors operating within or with smart mobile devices aim to accumulate health data in daily life outside medical institutions. Advances in computation capacities of mobile devices enable to process the collected data locally and in real time. In this way, mobile device users can see the results of sensed data in a human-readable format immediately. This empowers patients to observe health indicators in their normal daily life with comfort. Historical data of a patient can be aggregated for trend analysis and planned for the next step in a patient-specific cure. Any anomaly sensed by sensors can trigger an automatic event to inform related healthcare units or physicians for urgency situations. In addition to patients, non-patients can take the advantages of sensors utilized in mobile applications for tracking their diet or activity progress.

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E. Sezgin et al. (eds.), *Current and Emerging mHealth Technologies*,
https://doi.org/10.1007/978-3-319-73135-3_16

Another user group of mobile health applications is healthcare professionals who can employ several sensors to follow up their patients and to pick up electronic health records in medical processes.

There are a wide variety of sensor utilization examples in mobile health for different purposes and different user groups. Apart from basic sensor-based mobile health applications, more complex systems exist with more than one sensor in the form of wireless body sensor network in which sensors could communicate between them (Lo et al. 2005). Three main user groups are healthcare professionals, patients, and healthy individuals. Both patients and healthy individuals exploit sensor-based mobile applications for keeping personal health record (PHR). In this chapter, healthy individuals are represented by "non-patients" phrase. Healthcare professionals utilize this technology for tracking their patients. On the one side, healthcare professionals employ various sensors for tracking their patients. They use sensors for collecting health-related data in comfort zone of daily life. On the other side, non-patients use sensors and smartphone applications for tracking their fitness program, monitoring their calorie intake, and managing their weight (Azar et al. 2013). Independent from user groups and purposes of sensor-based mobile application, the usability of sensors within daily life plays a major role in user acceptance. Therefore, this study is structured to clarify the adoption of sensors in mobile health applications in terms of usability and its components. The adoption of sensors by patients and non-patients was studied in this chapter. Since the adoption of sensor-based mobile health applications for healthcare professionals is another broad concept to discover and deserves another study, it was excluded from this one.

All of the sensor types in mobile health and their adoption require attention when examining usability and user acceptance. Sensors and a mobile device that processes the sensed data together form an application. Users can reach sensed data within the user interface of the application running on a mobile device. Therefore, the performance of the application can affect user perceptions regarding usability. Moreover, processing and displaying capabilities of the mobile devices can also affect the user perceptions. Even a cutting-edge technology sensor can be seen non-usable and low acceptance level when used with poor applications.

Smartphones are the most popular mobile media with annual sales of over 1.4 billion around the world (Statista 2016). In order to concentrate on user adoption of sensors in a focused manner, therefore, the study is purposefully concentrated on sensors and their applications in smartphones.

In the first part of the study, sensors were briefly summarized and categorized into two main groups as add-in and built-in. Then, usability and user acceptance of sensors in smartphones were discovered in the chapter. For this purpose, four surveys were prepared and administered in 2016 with different user groups, and they are summarized in Table 16.1. In the first survey, usability and its components were examined, and add-in and built-in sensor groups were compared to understand their superiority. The second survey was designed to clarify the differences between non-patients and patients regarding usability perceptions. The third survey was aimed to determine the leading component of user acceptance for patients. The fourth survey was the replica of the third one, apart from the focus group as non-patients. There

Table 16.1 Aims, sensor type, user groups for the surveys, and experiments

Study type	Aim of the study	Used sensor type	User group
Survey 1	Adoption of sensors in mobile health with usability and its components (learnability, efficiency, memorability, errors, and satisfaction)	No restriction (all types: built-in and add-in)	Mixed (non-patients and patients)
Survey 2	Difference between usability perceptions of non-patients and patients	Built-in (hart rate detection based on PPG)	Mixed (non-patients and patients)
Survey 3	Most significant component out of learnability and efficiency for patients in terms of user acceptance	Add-in (blood sugar monitoring)	Patients
Survey 4	Most significant component out of learnability and efficiency for non-patients in terms of user acceptance	Add-in (chest band for heart rate monitoring)	Non-patients
Experiment 1	Role of ergonomics on user habits in the short term	Add-in (chest band for heart rate monitoring with different dimensions, weights, and materials)	Non-patients
Experiment 2	Role of ergonomics on user habits in the short term	Add-in (wearable cardiac monitoring T-shirt)	Non-patients
Experiment 3	Role of add-in and built-in sensors in user habits in the long term	Both (built-in pedometer and fake add-in sensor)	Non-patients

was no sensor limitation in the first survey to reach the maximum number of participants. However, other three surveys were actualized with specific sensors to eliminate the technological differences between various sensors. Since lightweight and more capable sensors are placed within each new smartphone model or provided as a brand-new additive component, the effect of their performance on usability perceptions was reduced by employing the same sensors for every survey respondents. Therefore, the following sensors were employed: built-in heart rate monitor, add-in blood sugar monitor, and chest band in the second, third, and fourth sensors, respectively. Moreover, all the sensors are assumed to be capable of sensing the related health data, and there are no problems related to performance originating from smartphones' processing capability, which affects usability and user acceptance. Furthermore, user adoption of wireless body sensor networks is left for future research.

In the next part of the study, user habits were studied based on human-sensor interaction perspective. In this part of the study, especially ergonomics was studied with three experiments for figuring out the effect of ergonomics on user habits, and they are listed in Table 16.1. The first experiment was about monitoring heart rate with chest bands in order to clarify the effects of different dimensions and materials. The second experiment was done with cardiac monitoring wearable T-shirt. The third one was executed with pedometers.

This chapter is organized into seven sections. The following section is devoted to the literature review of different sensor utilization examples in mobile health. The third section is reserved for the classification of sensors and examples. The fourth section is allocated with usability and user acceptance of sensors in mobile health. Human-sensor interface and user habits are examined in the fifth section. The findings are discussed in the sixth section. The study is summarized with propositions to help scholars and practitioners for designing new sensors or sensor-based applications for their future studies.

16.2 Literature Review

The literature on sensors and mobile health has various interest areas. Therefore, literature review is divided into subtitles for a more structured format. In the review, firstly, the focus is on user groups, which are classified as healthcare professionals, patients, and non-patients with different sensor-based applications. Subsequently, studies on challenges of sensor-based applications in smartphones are investigated. Lastly, studies on adoption of the mobile technology and sensors are covered.

16.2.1 Healthcare Professionals, Patients, and Sensors in Mobile Health

Early applications of mobile health just before smartphones focused mainly on developing special sensors that can be used with different mobile devices. The pioneering one was a portable personal data assistant (PDA) (McCracken 2012). Starting from the early 2000s, PDAs were utilized as a medium in the healthcare environment for remotely accessing health-related data or remotely collecting patient health records (Honeybourne et al. 2006). For this purpose, different PDA applications and their sensors were employed to collect health-related data. Among various examples, mobile nutrition tracking systems based on PDA for chronic kidney disease patients with low literacy skills are worth mentioning in this study (Siek et al. 2009).

The introduction of smartphones with better processing capability over PDAs yielded the gravity of mobile health applications onto smartphones. The advancements of data transfer rates in smartphones with the introduction of 3G and 4G networks have accelerated the development of mobile health applications based on smartphones. Afterward, special sensors have been designed to work with smartphones. These sensors are separate units that can be connected to smartphones. Mainly, they collect data and send it to the smartphone for processing and displaying measurement results. User groups of this kind of specialized add-in sensor-based bio-signal collecting mobile health applications are mainly healthcare professionals and patients. Even complicated body signals can be collected via portable electrocardiogram (ECG) for heart beats, electroencephalogram (EEG) for brain signals, and electromyogram (EMG) for muscles motions. As a use case, such sensors were designed and optimized to monitor elder people for collecting their vital health signals (Hu et al. 2009). Another multiparameter bio-signal sensor was able to collect ECG signal with one channel, temperature, photoplethysmography (PPG), and body fat within a single kit, such that two sensors could work simultaneously to collect two bio-signals at the same time (Kim et al. 2014). As another example, a body sensor network was proposed with Bluetooth data transfer capability for measuring physiological signals, interpreting results within a smartphone, and feeding back to users while employing optical pulse oximeter to detect heart beats and the saturation of oxygen (Wannenburg and Malekian 2015). Similarly, a medical sensor network was designed to collect health data of a chronic patient for intelligently supporting personalized healthcare (Korzun et al. 2015).

Some add-in sensors can be worn either as an attachment to clothes or alone, and they are called wearable sensors (Pantelopoulos and Bourbakis 2010). Since wearable sensors provide a comfort of collecting health signals within daily life without any extra effort, they are becoming more popular among mobile health consumers. An example is the cigarette smoking detection application which was developed on smartphone computing capabilities with the help of wrist-borne actigraphy and respiration chest (Dadkhahi et al. 2016). Another use case is the long-term usable and unobtrusive electrodermal activity assessment sensor (Poh et al. 2010).

16.2.2 Non-patients and Sensors in Mobile Health

Mobile health practitioners have been discovering the potential of non-patients. The users in this group are interested in monitoring their health and fitness level. This group of non-patients is called “motivated to be healthy.” They are dissimilar to the rest of non-patients who were detected as disinterested to use neither a mobile health application nor a sensor when they felt well and not willing to track their wellness level (Loo 2009). Therefore, the other non-patient group is distinguished with their motivation for tracking their health. They inspired scholars and practitioners to develop mobile health applications by utilizing built-in sensors of smartphones for wellness and health tracking without any known disease. One example was capturing a user’s running movement and modifying an audio file accordingly for synchronizing music rhythm with speed in order to motivate the user to run faster (Loungvara 2014). As an alternative to official measurements done by governors, non-patients become capable of collecting environmental data that may have some influence on their health. In this category, the exposure to air pollution level was measurable by all individuals with the help of an add-in sensor connected to smartphones for analyzing the level of polluting gasses in the air (Wang 2012).

16.2.3 Challenges of Sensor Utilization in Smartphones

Collecting and processing health signals via sensors uncover a difficulty in the smartphones with limited resources. Smartphones have limited battery, limited bandwidth, and limited processor capacity. A sensor should operate without consuming too many resources so that smartphones should operate for any other function including phone calls as well. To overcome this problem, low-power-consuming, low baud rate-occupying, and low processor-allocating applications were introduced based on fusing sensors with event-driven architecture (Lee et al. 2015). Similarly, the advantage of cloud computing for processing sensor-generated data was obtained for a path recommendation system of a wireless sensor network (Wanga et al. 2016).

16.2.4 Adoption of Mobile Technology and Sensors

The adoption of mobile health and wireless information technology is another main topic. Under this topic, computing standards, patient security and privacy, and electromagnetic compatibility can be covered. Although the adoption of sensor-based smartphone applications for patients and non-patients is the main focus of this study, it is worth mentioning healthcare professionals' critical role in adoption as the alignment of mobile health applications with their business objectives (Yu et al. 2006).

Like every technological improvement, perceived helpfulness of mobile health was determined as both positive and negative (Loo 2009). On the positive side, comfort, quality, and efficiency of healthcare with mobile health are determined. However, on the negative side, complexity and extra effort on individuals are the leading issues. Based on the background provided here, the classification of sensors in smartphones and their consumers' perceptions will be analyzed in the following sections.

16.3 Classification of Sensors in Mobile Health

In this section, sensors that work with smartphones for health applications are classified. Other sensors working on other mobile devices are excluded. This study proposes to categorize the sensors of smartphones used in mobile health into two main groups based on their physical existence: namely, "built-in" and "add-in." Built-in sensors represent the group of sensors produced as part of the smartphone, that is, they are manufactured as accessories for smartphones. Built-in sensors cannot be detached from the smartphone. On the contrary, add-in sensors represent removable sensors that are not part of the smartphone nor accessory. Add-in sensors

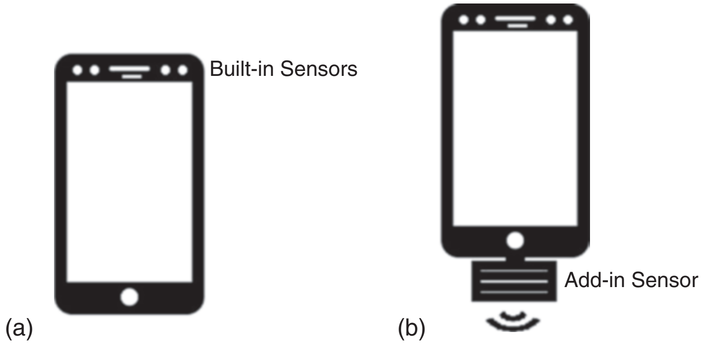

Fig. 16.1 (**a**) Illustration of built-in sensors like camera, light sensor, and microphone. (**b**) Illustration of an add-in sensor

can be produced by practitioners or scholars other than smartphone manufacturers. The simple illustration of sensor types is shown in Fig. 16.1. In the following subtitles, built-in and add-in sensors are explained in more detail with examples.

16.3.1 Built-In Sensors

Sensors in this group are produced within smartphones. They are installed by smartphone manufacturers. The sensors mentioned here may not cover all the sensors in all the smartphones. However, the list includes fundamental sensors. The primary purpose of the sensors in this group may not be measuring health-related data. Even so, the sensors can be used within mobile health applications for collecting health-related data. Main sensors can be listed as follows:

- *Camera* captures picture frames or videos. Since picture or picture-related data can be used to measure or detect health-related data, it is classified as a sensor. As a use case of this sensor, picture frames contain valuable data for PPG to detect heart rate and arrhythmia based on the fluctuation of blood level in vessels was examined (Altunel 2015).
- *Back-illuminated sensor* changes light captured while taking a photo. It works together with the camera and is a digital image sensor. As a use case, smartphones with these sensors were proposed as new low-cost optical imaging capabilities for diagnosing and monitoring treatments (Pratavieira et al. 2015).
- *Microphone* converts sound into electrical signals. It is an elementary part of all phones. As a utilization example, sound recorded by a microphone was used for the psychiatric assessment to monitor a user's behavior and mental health (Ben-Zeev et al. 2015).
- *Light sensor* measures ambient light level. It is used for tuning brightness level of the display. As a use case, light exposure of a smartphone user was estimated with light sensor (Wahl et al. 2014).

- *Accelerometer* measures the acceleration of a smartphone. In most cases, it also determines orientation along three dimensions. It can be used for counting the number of steps when there is no dedicated pedometer sensor. Gravity data can be derived based on accelerometer data. Sometimes gravity sensor is counted as a separate item. However, it does not exist in most of the smartphones. As a use case, therapeutic exercise performance was improved in terms of safety and efficacy with the use of this sensor and a smartphone application (Bittel et al. 2017).
- *Gyroscope* measures the orientation of a smartphone. Similar to accelerometer, it produces three-dimensional orientation data. However, gyroscope provides orientation data with better precision. As a use case, a fall detection and notification system was proposed for older adults (Wibisono et al. 2013).
- *Proximity sensor* detects the presence of objects nearby. It is an infrared sensor. As a use case, mobile spirometry for detecting chronic obstructive pulmonary disease (COPD) was utilized with the help of proximity sensor for detecting the distance between a smartphone and a patient (Zubaydi et al. 2017).
- *Global positioning system (GPS) sensor* determines location based on signals coming from GPS satellites. As a use case of GPS in mobile health, an Internet of things (IoT)-based gateway was designed for collecting location and health data for the analysis of intelligent personal assistants (IPAs) (Santos et al. 2016).
- *Magnetometer* measures magnetic fields of the earth. It is often used for compass applications. As a utilization example of the magnetometer, a real-time and remote edema monitoring application was proposed (Fallahzadeh et al. 2017).
- *Barometer* measures atmospheric pressure. Atmospheric pressure data can be used to determine altitude above the sea level. As a case study of the barometric pressure sensor in mobile health, a new methodology for recognition of vertical displacements in human activities was presented (Vanini et al. 2016).
- *Thermometer* measures air and body temperature. This sensor was grouped with an electrocardiogram (ear-lead ECG) for monitoring body temperature, heart beats, and oxygen saturation (Manivannan et al. 2016).
- *Air humidity sensor* measures air humidity level. Environmental data as well as humidity was collected via this sensor for enabling the convenient health management of elders (Noh and Cha 2016).
- *Fingerprint sensor* is included in various smartphones and used for providing extra security in terms of biometrics. This sensor was evaluated for privacy perspective as a part of the personalized mobile health architecture (Siddiqui et al. 2014).
- *Radiation detector* measures the level of harmful radiation in an environment. It is available only on some smartphones in Japan. Such a sensor has been installed after Fukushima Nuclear Disaster (Ishigaki et al. 2013).
- *Heart rate sensor* measures heart rate based on PPG. It is included as a separate unit, only in few smartphone types. This sensor was performed acceptable when compared to other heart rate mediums in terms of heart rate variability (Plews et al. 2017).

16.3.2 Add-In Sensors

Sensors in this group are specialized ones to collect specific health-related data. These sensors are not part of smartphones. They are produced by scholars or practitioners other than smartphone companies. Add-in sensors either are connected to a smartphone or communicate with a smartphone via a wireless protocol. Add-in sensors can be designed as an accessory or a separate unit. Since add-in sensors are specialized ones developed to collect specific health data, there are various sensors which are not standard or similar under this group. Therefore, they are divided into the following two subgroups in terms of categorization. The first subgroup is uni-sensors which are add-in sensors specialized on a unique health signal. The second group is multi-sensors which can measure multiple health signals on the same device. The subgroups are explained in more detail with examples below:

- *Uni-sensors are sensors with measurement capability of only one type of health signal.* As an example of the commercialized accessory is the one channel ECG that was designed as a case for some smartphone models and available in the end consumer market (Alivecor 2016). As another use case, a smartphone can operate as a portable chemical laboratory like blood sugar monitoring device with the help of a connected uni-sensor (Iqbal 2011). Although blood sugar monitors were designed to be used alone, some of them could communicate with smartphones to keep a record of history (Tran and Tran 2012). Similarly, cholesterol level in the blood could be determined within seconds by a uni-sensor connected to a smartphone and an application detected the level on the strip (Oncescu et al. 2014). The acidity level in saliva and sweat could also be measured by the sensors specialized on biomarkers that were attached as an accessory to the smartphone (Oncescu et al. 2013). Moreover, a smartphone camera was turned into a portable digital microscope by attaching a convex lens with the help of an adapter (Sumriddetchkajorn et al. 2012). Uni-sensors in mobile health domain can be used for measuring indirect health-related data other than direct physiological ones such as air or water pollution. An example of such sensors was designed to detect the mercury contamination in water by a specialized sensor attached to a smartphone (Wei et al. 2014).
- *Multi-sensors* can detect more than one health-related data. As an example, PPG, electrodermal activity (EDA), triple-axis accelerometer, and temperature sensors were combined to form a small and light multi-sensor for real-time computerized biofeedback and data acquisition (Garbarino et al. 2014). For heterogeneous sensor applications, a reconfigurable multisensory mobile interface was introduced as readout integrated circuits (Choi et al. 2017). Even a wearable form of a multi-sensor with human body harvesting and without any battery requirement was announced recently (Magno et al. 2016). Wearable multi-sensors were prepared for patient self-assessment and monitoring (Appelboom et al. 2014).

16.4 Testing Usability and User Acceptance of Sensors

Usability is defined as how easy a user interface is to use (Nielsen 1993). It is a quality attribute and different from the other attributes. It has five basic components: learnability, efficiency, memorability, errors, and satisfaction. A brief explanation of each component adapted for sensors in mobile health is provided below:

- Learnability: For users, how easy to accomplish basic tasks the first time they encounter the sensors?
- Efficiency: For users, how quickly to perform tasks with the sensors?
- Memorability: For users, after a period of not using them, how easy to reestablish proficiency on the sensors?
- Errors: For users, how many errors do they make when using the sensors, how severe are these errors, and how easy do they recover from the errors?
- Satisfaction: For users, how pleasant to use the sensors?

16.4.1 Usability Results

For the evaluation of adoption of sensors in mobile health, this study used components of usability. For this purpose, a questionnaire was prepared to include questions addressing each usability component listed in Table 16.2, based on the five evaluation components of the usability determined by Brinck et al. (2002). For each component, a direct question was asked to understand the perceptions of users. An additional question was employed to ask for overall usability of the sensors. Demographic questions including age, gender, and type of sensors were asked as well. A total of nine questions including demographic ones was used. The survey was kept short in order not to bother respondents, to get higher participation, and to

Table 16.2 Usability questions in the first survey

Learnability	Was it easy to learn how to use the sensor, when you first encountered the design?
Efficiency	Was it fast to perform a measurement with the sensor and get the result on the application?
Memorability	Was it easy to memorize sensor usage and basic features after giving 1 week or more pause?
Errors	Was it possible to recover an error made by you during the usage of the sensor?
Satisfaction	Was it a pleasure to use the sensor and the related application?
Overall usability	When you think of your overall experience, was it easy to use the sensor?

Based on the usability components by Brinck et al. (2002)

keep data quality of the survey better (Groves et al. 1992; Mavletova 2013). Each question was formulated in the same structure and asked for the results of experience with the sensors.

The answers were prompted with a 5-point Likert-type scale (Likert 1932). One (1) point means "definitely no," 2 points "probably no," 3 points "unsure," 4 points "probably yes," and 5 points "definitely yes." If a respondent answers all the questions by giving 5 points, then it means the sensor gets highest usability score possible. Functionality and performance of the sensors were assumed to be same for the first survey.

The first survey was organized in electronic form and sent to a total of 557 mobile health application users without caring about sensor types and related applications. These participants were selected randomly from active mobile health application users. Only 141 people responded to the survey during March and April in 2016, and response rate of 25.3% (n = 141) was obtained. None of the responses was deleted from the dataset. Responses coming after the 30th of April could not be included in the study. Thus, the final dataset consisted of 141 replies.

The average age of the respondents was 25.7 (n = 141) with standard deviation of 4.9. Only 17% (n = 24) of the respondents were women, whereas 82.9% (n = 117) of them were men. The results are categorized according to the type of sensor as built-in and add-in, based on the classification defined in the previous section, and they are shown in Table 16.3. Of the respondents, 73% (n = 103) are grouped under built-in sensors, whereas 27% (n = 38) of the respondents are categorized within add-in sensors. Mean values of the responses for each question are listed in Table 16.3. Scores for the built-in sensors are slightly higher than scores of the add-in sensors. In addition, the gap between scores of sensor types is highest for the learnability component. These two results may be due to the extra process steps to connect an add-in sensor to a smartphone, which is an additional activity for the user. This subject will be examined in the next section. Moreover, the gap between two sensor types is lowest for the efficiency component. The highest score for add-in sensors was given for the efficiency component. Independent from add-in sensor

Table 16.3 The results of the first survey

	Mean values of the survey results for built-in sensors (with standard deviations in parentheses)	Mean values of the survey results for add-in sensors (with standard deviations in parentheses)
Learnability	4.5 (0.3)	3.6 (0.5)
Efficiency	4.4 (0.4)	4.3 (0.2)
Memorability	4.2 (0.4)	4.1 (0.2)
Errors	3.7 (0.5)	3.5 (0.3)
Satisfaction	4.3 (0.4)	3.9 (0.3)
Overall usability	4.4 (0.4)	4.2 (0.3)

type, a portable and smartphone compatible sensor may provide an increment in efficiency compared to conventional measurement and tracking systems. For both sensor groups, the lowest scores were given to the error component, which indicates the difficulty in recovery of errors when comparing to other usability components.

The second survey was designed to examine the difference between usability perceptions of non-patients and patients. For this purpose, in order to eliminate different user habits between different sensors, one built-in sensor and its application were chosen. The built-in sensor was the camera with its application of detecting heart rate and arrhythmia based on PPG (Altunel 2015). The application was used either by non-patients to track their heart rate or by patients who were suffering mainly from arrhythmia problems. Same questions for usability and its components were asked as in the first survey. Two more questions were employed to detect the frequency of usage and comparison with an alternative way of detecting heart rate as in Table 16.4. An additional question was asked to clarify the dominant usability component when the sensor with the smartphone was found as more useful when compared to conventional measurement approaches.

The second survey was responded by 34 people during April and May in 2016. The expectancies of the respondents were assumed to be satisfied with the sensor and its application in terms of health perspective. Two users with different needs than the capabilities of the sensor and the application were eliminated from the survey results. As an example, there was the atrial fibrillation patient for asking to detect his period of arrhythmia which was out of the capabilities of the application, and therefore, he was not invited to participate into the survey. The remaining survey respondents were assumed to be satisfied with health performance. The social influence of using a sensor and a smartphone on individuals was assumed to be the same, and this topic deserves another research. Hence, the final dataset was composed of 32 responses.

Table 16.4 Additional questions for the second survey

Frequency	How often do you use the sensor and the application?	1. Less than once in a month 2. Once or twice in a month 3. Once in a week 4. Couple of times in a week 5. Everyday
Comparison	Did you find the sensor and the application more useful than other conventional measuring and tracking systems?	1. No 2. Yes
Comparison extending question	If your answer to the previous question is "yes," then in what way was it useful?	1. Easier to learn 2. More efficient to perform a measurement 3. Easier to memorize 4. Easier to recover when an error occurs 5. More pleasure when using

Table 16.5 The results of the second survey

	Mean values of the survey results for non-patients	Mean values of the survey results for patients
Learnability	4.3	3.9
Efficiency	4.2	4.2
Memorability	4.2	4.0
Errors	3.9	3.8
Satisfaction	4.1	4.0
Overall usability	4.2	4.1

Table 16.6 The results of the extra questions in the second survey

	The most popular answer for non-patients	The most popular answer for patients
Frequency	4. Couple of times in a week	5. Everyday
Comparison	2. Yes	2. Yes
Comparison extending question	1. Easier to learn	2. More efficient to perform a measurement

The average age of the respondents was 39.2 ($n = 32$) with the standard deviation of 5.6. Only 25% ($n = 8$) of the respondents were women, whereas 75% ($n = 24$) of them were men. Of them, 68.8% ($n = 22$) have declared themselves as healthy, whereas remaining 35.2% ($n = 10$) were recorded as patients.

The results of the second survey are presented in Table 16.5. The first finding is the slightly higher scores given by the non-patients for the components of usability. To understand the underlying reason for the higher scores of non-patients, two user groups are compared in terms of age, gender, and experience, which were found as the moderation factors for behavioral intention and usage behavior for technology (Venkatesh et al. 2012). There was an observable difference only in the ages of the survey respondents. The mean age of the healthy group was 33.2 ($n = 22$) with the standard deviation of 4.5. While the patient group was 39.7 ($n = 10$) with the standard deviation of 3.2. As the second corollary, the error component was given the lowest scores from both user groups similar to the previous survey.

The extra questions for the second survey were answered by 100% ($n = 32$) of the total participants. The results are shown in Table 16.6. Since the patients were motivated to track their heart rate more closely, the frequency of usage for the patients was found higher than the non-patients. Both groups were in favor of using a sensor and a mobile application combination rather than using any conventional tracking system. However, the main reasons were different. The non-patients and the patients have chosen different usability component. The non-patients were in favor of learnability, whereas efficiency was selected by the patients. Since non-patients use mainly the heart rate measurement capability of the sensor and the application, learning easily to measure the heart rate plays a major role of being useful when compared to conventional heart rate measurement systems like ECG, heart rate monitor, and pulse oximeter.

16.4.2 User Acceptance Results

Technology user acceptance is modeled in the technology acceptance model (TAM) (Davis 1986). TAM is extended to define perceived usefulness and ease of use, which were found as the main determinants of user acceptance in information technology (Davis 1989). Performance, productivity, and effectiveness are the main factors behind perceived usefulness. Perceived usefulness in our case can be defined as the degree to which one believes that using a sensor with a mobile application will enhance performance. This definition mainly addresses the efficiency component of usability. Although there are various factors determining ease of use, ease of learning was found as the far most relevant one (Davis 1989). Therefore, ease of use can be affected by the learnability component of usability. Based on this knowledge, the most significant components for user acceptance were declared as learnability and efficiency. Hence, this study focused on them. In order to compare their roles in user acceptance, another questionnaire with one question was prepared as in Table 16.7.

The third survey was sent to 148 people and responded by 60.1% ($n = 89$) people between May and July 2016 with the average age of 46.7 with the standard deviation of 6.1. The respondents were users of add-in sensors for measuring and recording their blood sugar level. The type and model of the sugar level monitors could be different. However, the usage of the sensors and the smartphone application was the same. Of the respondents, 97.7% ($n = 87$) declared themselves as patient whereas 2.3% ($n = 2$) of them healthy. Getting a special sensor for blood sugar level monitoring is peculiar to people with diabetes. The answers of only two participants are not representative of non-patients and cannot be generalized. Therefore, the responses of two non-patients were excluded from the analysis, and the final response set consisted of 87 answers.

The results were exhibited in Table 16.8. Efficiency was scored higher than learnability. Hence, it can be concluded that efficiency is the major component of user acceptance. This result is in parallel with the Robey's expectancy model that declared the 0.79 correlation between usage and performance, which was one of the dominant factors of efficiency (Robey 1979). For built-in sensors, the highest score

Table 16.7 The user acceptance question

User acceptance factor	Which one is the most important factor for you to choose this sensor and its application?	1. Learning easily 2. Using efficiently

Table 16.8 The results of the third survey for patients

	Number of people in favor a specific answer	Percentage within the whole group
Learnability	39	44.8
Efficiency	48	55.2

Table 16.9 The results of the third survey for non-patients

	Number of people in favor a specific answer	Percentage within the whole group
Learnability	25	53.2
Efficiency	22	46.8

was given to efficiency by patients as shown in Table 16.4. Thus, the dominant role of efficiency in user acceptance can be proposed to be valid for patients, independent of the sensor type.

In the fourth survey, the same procedure in the third survey was repeated by 92 invited people for clarifying user acceptance from non-patients' perspective. Only 51% (n = 47) of them replied the survey between June and August 2016 with the average age of 32.5 with the standard deviation of 4.5. The respondents were non-patients using an add-in sensor for measuring heart rate with a chest band and an application on a smartphone (Altunel 2015). They have used the chest band and the mobile application mainly during a fitness activity. The results were presented in Table 16.9. Learnability was the favorite answer of the 53.2% of the group, which underlines the dominance of it on efficiency for non-patients.

Based on the third and fourth survey results, diverging priorities of patients and non-patients in terms of user acceptance become clear. Scholars and practitioners working on new sensors and smartphone applications should take into account the learnability expectation of non-patients while efficiency expectation of patients.

16.5 Testing Human-Sensor Interaction and User Habits

Human-computer interaction (HCI) is adapted to sensors world with human-biometric sensor interaction (HBSI) (Dix 2009; Brockly et al. 2014). In HBSI area, usability and ergonomics were two main dimensions of sensor-human interaction evaluation (Kukula et al. 2010). Usability was examined with its components in the previous section. Since ergonomics is lying just at the intersection of human and sensor in the HBSI model, this part of the study will focus on ergonomics, which can be defined in our context as designing and arranging sensors and their applications so that people can use them easily and safely (Wilson 2000). In this context, ergonomics defines human-sensor interaction and comfort with sensors. On the account of this, a successful sensor in a mobile health application needs to take into consideration how users interact with a device. Physical, behavioral, and social factors of users influence ergonomics and human-sensor interaction. In this chapter, these will be assumed to be constant, and only the sensor-based factors for interaction will be studied.

Fig. 16.2 Chest band and smartphone system for understanding ergonomics of the sensor

16.5.1 Testing Set-Up

The shape, weight, and size of sensors play primary roles in the human-sensor interaction (HSI). If a sensor is a built-in type, then these parameters could not be directly applied. In this case, effective utilization of a built-in sensor in a mobile application plays a major role in the HSI. If a sensor is an add-in type, then the shape, weight, and dimensions of the sensor play significant roles in ergonomics.

In order to understand the role of ergonomics on user habits, an experiment was set up with a chest band heart rate monitoring system, illustrated in Fig. 16.2. In the experiment, the sensor within the chest band was kept the same, while the cover of the chest band was changed in terms of weight, shape, and dimensions. The sensor on the chest band stored data in a memory unit. After finishing the experiment, it was connected with a smartphone and sent the measured data to make necessary processing for determining the heart rate.

16.5.2 Results of Human-Sensor Interaction and User Habits

A football team with all 18 members with the mean age of 22.4 with the standard deviation of 1.2 were invited, and all of them attended the experiment in April 2016. The team members were asked to carry a chest band while training and running. The training was planned to last for 2 h. They were also informed of the positive value of taking heart rate during the whole training for further analysis. However, they were let free to remove the chest band when they felt any discomfort. The heart rate sensor with different covers in the form of the chest band was given to the team members (see Table 16.10). The time elapsed until the removal of the chest band was measured for each cover and shown in Table 16.10. The weights shown in Table 16.10 are the total weights of the sensor and the chest band together.

Two materials were chosen as cotton and acrylic. Cotton bands were softer whereas acrylic ones were harder but more durable. The width of the bands was the same as in the 1st and 2nd band types, and the effect of material type was targeted

Table 16.10 The results of the first experiment on ergonomics with heart rate monitoring

Chest band type number	Chest band cover	Number of team members	Mean of the duration for carrying chest band (min)	Number of team members for using the chest band till the end of the training
1st	2 cm wide, 120 g, made of cotton	4	86′	1
2nd	2 cm wide, 90 g, made of acrylic	4	75′	0
3rd	4 cm wide, 220 g, made of cotton	4	81′	0
4th	6 cm wide, 120 g, made of acrylic	3	59′	0
5th	2 cm wide, 1210 g, made of cotton (with hidden extra weights)	3	47′	0

to be observed. Even though acrylic bands were lighter, cotton bands were used for longer duration as shown in the fourth column of Table 16.10. The materials of the bands were the same for the 1st and 3rd types as cotton. The effect of width was aimed to be investigated. As expected, when the width of the bands was doubled, the band removal duration decreased. The effect of width was compared for acrylic bands between the 2nd and 4th types. The width of the bands was tripled, and in response, the band removal duration declined dramatically. The effect of weight was compared to cotton bands between 1st and 5th types. The shape, material, and width were kept the same. However, extra weight was added to the bands under 5th type. Extra weight caused the lowest band removal duration for the 5th type. Only one team member carried the chest band which was made of cotton, until the end of the experiments. This experiment shows the importance of material type, dimensions, and weight of the sensor for mobile health applications.

The first experiment was repeated with the same team 3 weeks after. In this experiment, Cardio Leaf, which was a wearable cardiac monitoring T-shirt of Clearbridge VitalSigns, was utilized (ClearBridgeVitalSigns 2016). Since there were limited samples, team members wore them in turn. Thirteen team members carried the wearable sensor until the end of the training, and the mean duration of removal was 114 min, which was considerably higher than the chest band cases. It is possible to conclude that wearing a sensor-based T-shirt instead of a normal T-shirt was widely accepted by the team members. This finding underlines the importance of providing sensors in wearable forms instead of providing as an extra equipment (Pantelopoulos and Bourbakis 2010). Similar to sensor-based T-shirts, some smart watches and wristbands have health-related built-in sensors that can be carried in replacement of a normal watch. Replacing a daily cloth or an accessory with a sensor-based one is much easier than adding an extra sensor to daily life. Thus, daily clothes with sensor-based capabilities is a major improvement in terms of the human interaction of sensors for mobile health.

After providing ergonomics of sensors in mobile health for users in daily life, user habits play a role in the acceptance or rejection of a related sensor or technology for collecting health-related data. For accumulating user habits of mobile users, a new approach is introduced based on data mining (Cao et al. 2010). For context-aware mobile systems, an intelligent middleware layer is proposed between the sensor layer and the inference layer in order to understand user habits for adjusting sensor sampling rates and minimizing power consumption (Bobek et al. 2013). The effect of augmented reality (AR) on user behaviors in mobile health is studied with a game, and in the long term, AR cannot provide sustained behavioral change for a healthy lifestyle (Kosoris and Chastine 2015). However, there is no direct study on user habits for HSI in mobile health.

In order to understand user habits with sensors, the third experiment was conducted in May 2016. In this experiment, a pedometer application utilizing accelerometer and gyroscope was used. The pedometer application was able to count steps for a given period and capable of showing a trend day by day. Users of the application were divided into two groups. Of the participants, 52.2% ($n = 12$) were in the first group, whereas 47.8% ($n = 11$) were in the second group. All participants were selected randomly, and they declared themselves as healthy with the mean age of 24.6 with the standard deviation of 2.3 and 25.2 with the standard deviation of 3.1, respectively. The first group was given just the software, and they deployed it into their smartphone for using as a pedometer. The second group was given the same software and an extra device which was introduced as the sensor for the participants in the group. However, the device was nothing to do for sensing steps or movements. Duration of the usage was recorded in minutes for both groups. The mean duration of the daily usage for each group throughout the first 15 days was shown in Fig. 16.3. The number of active users of the application during the first 15 days was shown in Fig. 16.4.

As can be seen from Fig. 16.3a, b, total usage of the application decreased dramatically in the first 7 days and then saturated afterward. When two groups are compared, the application was used longer in group 1 than group 2. This indicates the negative motivation created by an additional device in the form of sensor.

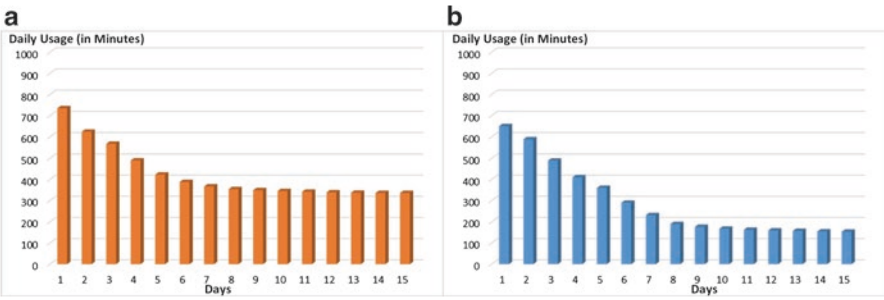

Fig. 16.3 (**a**) Daily usage of the application for user group 1. (**b**) Daily usages of the application and the extra device for user group 2

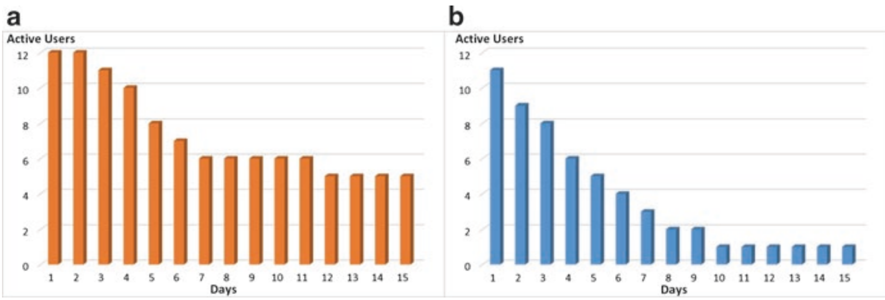

Fig. 16.4 (**a**) Number of active users in group 1. (**b**) Number of active users in group 2

In Fig. 16.4, decrement in the total number of users in both groups is obvious. In group 1, after 15 days, five users were using the system, whereas only one user was using in group 2. Therefore, the loyalty between two user groups was different. This can also be due to the difference between built-in and add-in sensors.

16.6 Findings

In order to discover the adoption of sensors used with smartphones for mobile health applications, results of the previous sections are examined in this section. All of the surveys and experiments are listed with their findings in Table 16.11, as a summary.

The results of the surveys on the usability of sensors in Sect. 16.4 emphasize the importance of the learnability and efficiency components of usability. Therefore, the scholars and practitioners are invited to take into account this finding. However, this does not mean that memorability, errors, and satisfaction components are not important. In order to understand the relationship with the overall usability, statistical analysis was utilized (Dixon and Massey 1957). The correlation between overall usability and the components were calculated based on each respondent's answer, and the result is shown in Table 16.12.

As shown in Table 16.12, in all surveys, all components have a strong positive correlation with usability. The satisfaction component has the highest correlation values with usability after learnability and efficiency. Especially, for non-patients, the value was 0.77, which indicates a strong positive correlation. For patients, the result of 0.68 indicates a strong expectation of satisfaction from survey respondents. Independent of add-in or built-in type sensor, correlation values over 0.70 underline the importance of giving pleasure to consumers with a nice sensor design.

The memorability component has a slightly lower correlation with usability than satisfaction. Patients have the highest correlation value. Chronic patients should use medication or medical device for a long period of time. They may use medical devices or sensors time to time, and they should remember how to use sensors each time.

Table 16.11 Number of participants and the results of the surveys and experiments

Study type	Number of participants	The results
Survey 1	141	Built-in sensors have slightly higher usability scores than add-in sensors The highest score for built-in sensors is for learnability component The highest score for add-in sensors is for efficiency component The lowest scores for both types of sensors are for errors components
Survey 2	32	Non-patients give higher scores than patients Both non-patients and patients prefer sensor-based mobile applications than using any other medical tracking system
Survey 3	89	For patients, the most important factor of user acceptance is efficiency
Survey 4	47	For non-patients, the most important factor of user acceptance is learnability
Experiment 1	18	Dimensions, weight, and material of a sensor play a role in user habits
Experiment 2	18	Wearable sensors are accepted by the users better than other add-in sensors
Experiment 3	23	Built-in sensor-based applications have a higher potential of becoming a daily user habit than add-in sensors

Table 16.12 Correlation between usability and its components

	Built-in sensors (Table 16.3)	Add-in sensors (Table 16.3)	Non-patients (Table 16.5)	Patients (Table 16.5)
Corr. (learnability, usability)	0.87	0.79	0.84	0.74
Corr. (efficiency, usability)	0.82	0.84	0.78	0.89
Corr. (errors, usability)	0.52	0.53	0.55	0.51
Corr. (memorability, usability)	0.67	0.66	0.69	0.71
Corr. (satisfaction, usability)	0.73	0.72	0.77	0.68

The results on memorability in Table 16.12 demonstrate that non-patients also need to recall easily sensors. This situation is valid for both add-in and built-in sensors, and it clarifies the simple and easy to remember sensor design expectation of patients.

The errors component had the lowest correlation with usability from all groups without any exception. Hence, it can be proposed that in all user groups, people have faced with some errors, and they learned how to live with errors within mobile world. This does not mean of providing a sensor and an application with bugs and problems to end customers. Rather providing a sensor and an application in an error-free format is important, and mobile health consumers can tolerate small errors that they can handle.

In Sect. 16.4, user acceptance in patients and non-patients was studied with a survey utilized for the add-in blood sugar monitors. Learnability and efficiency were two dominant components of user acceptance. For non-patients, the highest correlation between usability and its components was obtained by learnability with 0.84 in Table 16.12. This is in parallel with the results in Table 16.8. For patients, the highest correlation was obtained by the efficiency component with 0.89 in Table 16.12, verifying the results in Table 16.8.

For discovering human-sensor interaction, ergonomics was studied with different shapes, weights, and materials on a football team. Although 18 people in a football team could not be a proper group size for discovering ergonomics, the results clarified the tendency of using wearable sensors instead of carrying an extra sensor in any case. HSI and ergonomics deserve further experiments and studies to figure out underlying dynamics for designing optimal sensors for daily life.

The third experiment with a pedometer application among non-patients demonstrates the decreasing motivation of individuals in using a new technology and gaining a new habit. This outcome underlines the difficulty of putting practice into a habit (Gardner et al. 2014). Only a few participants continue using the application and the sensor after the first week. Five people were endured until 15 days of experiment observation period in the add-in sensor case. By contrast, only one person used the system with built-in sensor until the end of the experiment. These people in both groups demonstrated the highest perseverance and can be a sample of non-patients with highly motivated to stay on the healthy side (Ribeiro et al. 2016).

The surveys and experiments focused on sensors in mobile health. However, other physical factors could affect results. First factor is an application working with a sensor. Since a sensor and a mobile application together form a system for serving customers, the overall performance of the system is influenced by the application as well. In some cases, mobile applications running on smartphones operating with sensors dominate usability and user acceptance perceptions of end users. The second one is a smartphone itself. Processing capacity, screen resolution, and other features of a smartphone may have an impact on the overall evaluation. In order to eliminate these effects in further studies, surveys and experiments can focus on a specific smartphone model. Nevertheless, this may narrow respondents in surveys and volunteers in experiments, and so results become no more representative.

Different sensors and their applications can initiate different perceptions on different people. In order to evaluate the HSI in a wider context, distinct sensors and their applications were employed in the surveys and experiments as heart rate monitors, blood sugar monitors, and pedometers. To explore the impact of different sensors, diverse sensors and their applications can be utilized in future studies.

All the surveys and experiments were realized in Turkey in the first half of 2016. Demographic conditions, social factors, and user habits in Turkey could influence the results, and they were assumed to be stable. Although participants were selected randomly, the number of participants in the surveys and experiments were limited. Therefore, more surveys and experiments with larger participant groups around the world are required to check the validity of the results in this study.

16.7 Conclusion

In this study, sensors in mobile health are classified into two main groups, namely, built-in and add-in. The usability and user acceptance of sensors in mobile health applications among patients and non-patients were studied with surveys and experiments. User habits were disclosed with the help of statistics derived from the survey results. The first finding of the study is the importance of learnability of sensors and their applications for non-patients and that of their efficiency for patients. Chronic patients are more used to utilize sensor-based applications than non-patients in their daily life. However, "motivated to be healthy" people are also caring about their health and wellness status. Therefore, sensor-based applications for non-patients should primarily take this group into consideration.

The second finding is preference for built-in sensors instead of add-in due to unwillingness of people to carry an extra device in the sensor form. As an additional finding, in the case of necessity of using add-in sensors, wearable sensors are more credible than ones in the device form. When it is not possible to implement a wearable sensor, an add-in sensor should be designed to take ergonomics into account. Especially weight, dimensions, and material of the sensor play a role in the adoption of sensors. Scholars and practitioners designing sensor-based mobile applications are advised to take these findings into consideration.

This study presented the results of the surveys and the experiments with a limited number of participants for examining the adoption of sensors in mobile health. In further studies, larger groups of people can be included. In this way, demographic, geographic, and social effects on user acceptance and user habits can be clarified as well. Another area to investigate is the adoption of sensor-based mobile applications for healthcare professionals. Moreover, with the diffusion of wireless body sensor networks, adoption studies can be executed on them as well.

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Chapter 17
Adoption of Internet of Things in Healthcare Organizations

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17.1 Introduction

The Internet of things is a new paradigm that enables integration and communication of things or objects such as radio-frequency identification (RFID) tags, sensors, actuators, mobile phones, etc. (Atzori et al. 2010). IoT devices are defined as cyber-physical devices which can operate in any context by its sensing, communicating, and processing capability (Cicibaş and Demir 2016). It is expected that IoT will provide novel solutions to transform the operation and role of industrial systems (Xu et al. 2014). In modern industry, these devices are being used for many purposes in terms of monitoring, tracking, data collection, and analyzing. Some preliminary IoT applications have been already implemented in several areas such as healthcare, public services, and automotive industries. Among these areas, the cost projection of IoT healthcare applications will be around 1 trillion dollars by 2025 (Manyika et al. 2015).

In healthcare perspective, IoT domain serves as a generic platform for exchanging information between mobile health (mHealth) devices and various ubiquitous technologies. IoT provides processing data which are collected by different types of devices such as mobile devices, implantable devices, wearable devices, and ambient-assisted living solutions. Therefore, IoT concept is a bridging architecture for mHealth technology through its IP-based connection capabilities.

The role of IoT in the mHealth domain can be explained by a simple example. By the aid of local area network communication technologies (e.g., Bluetooth, WI-FI, etc.), data which was collected by sensors deployed in patient's body are

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E. Sezgin et al. (eds.), *Current and Emerging mHealth Technologies*,
https://doi.org/10.1007/978-3-319-73135-3_17

transmitted to the mobile devices (e.g., mobile phone, hub, etc.) of the patient. Then the mHealth application processes and send this data to a central database. By using another mHealth application, healthcare professionals access this database, diagnose, and may send instructions to the patient. In addition, this data is processed automatically by advanced tools to detect anomalies about the patients. IoT ensures communication and integration of these mHealth entities (sensors, devices, and applications) mentioned in this example. Regarding such a scenario, the impact of IoT concept on mHealth is crucial, and more effort is required to understand the relation between IoT and mHealth. We believe that effective use of mHealth technologies can be only achieved by using advanced IoT solutions. Successfully deployed and widely adopted IoT devices would increase the quality and amount of data which is considered as the main source of mHealth applications.

In literature, the impact of IoT on mHealth is investigated by several studies (Istepanian et al. 2011; Santos et al. 2014, 2016). These studies propose some theoretical models for integrating IoT capabilities into mHealth applications. The motivation of these works is nourished by the potential benefits of IoT capabilities which are expected to bring superior abilities to healthcare by enabling mHealth solutions. Existing studies have also proved this expectation by showing reduced costs and increased efficiency in IoT-enabled healthcare services (Couturier et al. 2012). In addition, IoT and its enabling technologies minimize healthcare failures such as medical mistakes, theft, loss, drug counterfeiting, and inefficient workflow (Yao et al. 2010). However, despite the increasing trend and its benefits, IoT devices are not fully integrated into healthcare organizations. One of the most important reasons for the lack of integration is the low adoption level of these technologies by the users. Regarding this open issue, more research is needed to investigate main variables that influence the decision to adopt these technologies.

Adoption of ICT systems in healthcare is examined in previous studies (Ahmadi et al. 2015; Bärenfänger et al. 2014; Chong et al. 2012; Howells and Wood 1995; Kijsanayotin et al. 2009; Lee and Shim 2007; Matalka et al. 2009; Rickerby 2006; Spanjers et al. 2005; Venkatesh et al. 2011; Wong et al. 2000; Wu et al. 2007, 2011). These studies analyze adoption of ICT systems such as RFID, electronic medical record, electronic patient record (EPR), clinical information system, telemedicine, smartphones, electromagnetic healthcare systems, and other RFID systems in healthcare. They use technology acceptance models and theories presented in technology adoption literature. Although these studies have fruitful contributions on adoption, none of them deal with IoT implementations in healthcare. In addition, most of them do not classify decision variables regarding different types of users perspective.

Although, Ahmadi et al. (2015), Dey et al. (2016), Fosso Wamba et al. (2016), Kuo and Chen (2008), and Lu et al. (2013) classify these variables in different dimensions such as organization, environment, and technology, they are insufficient to focus on the diversity of users' beliefs. In this study, we focus on the adoption of IoT devices in the healthcare domain. We present a detailed analysis of factors that affect the adoption of IoT concept regarding different types of users' perspective. The contributions of this study are (i) to close the gap in literature by addressing IoT adoption in healthcare; (ii) to help decision-makers to understand the main variables which affect adoption decision among different users in terms of top level managers, healthcare professionals, technical staff, and patients; and (iii) to present recommendations for healthcare managers to improve the adoption process of IoT devices in their organizations.

This paper is organized as follows. Section 17.2 illustrates review methodology of our study. Section 17.3 presents the impact of IoT technologies on mHealth. Section 17.4 describes an in-depth review of main factors that affect technology acceptance decision in the healthcare domain. In Sect. 17.5, recommendations for the managers are presented. The conclusion is given in Sect. 17.6.

17.2 Methodology

17.2.1 Review Methodology

We have conducted a literature review on academic databases. We used the following search parameters in ScienceDirect, IEEE Xplore, and Web of Science. We also used Google Scholar to support these databases. In our search query, we used three phrases with logical operators and limit the search with the articles published between 2007 and 2017. Since RFID seems as a prerequisite for the IOT domain (Jia et al. 2012), "RFID" term is also used in the search query. The number of articles which were found in academic databases is presented in Table 17.1. This work was conducted in May 2017; therefore, the number of articles published in 2017 is less than other years. We used the following search query in our search:

$$\left\{\begin{array}{c}\left(\text{" Internet of Things" VIoTVRFID}\right)\wedge \\ \left(\text{healthcareV health V hospital V medical}\right)\wedge \\ \left(\text{acceptance V adoption V" technology adoption "V" technology adoption"}\right)\end{array}\right\}$$

Table 17.1 Number of papers after refining procedure

Database	Database fields	Number of papers before first phase	Number of papers before second phase	Number of papers before third phase
Science Direct	Titles, abstracts, and keywords	29	15	13
IEEE Xplore	Metadata only	64	22	17
Web of Science	Titles, abstracts, and keywords	116	24	10

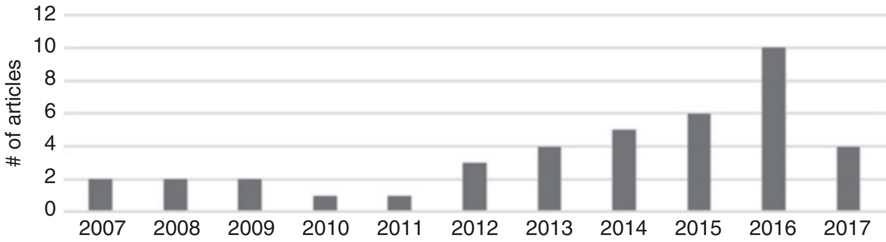

Fig. 17.1 Number of Articles Addressing IoT and RFID adoption in healthcare

We used a refining procedure which is similar to the method presented by Sezgin and Yildirim (2014). After the refining procedure, we selected 40 articles. Addition to these articles, we also surveyed the references of these studies. The steps of this procedure are described as follows:

Phase 1: Abstracts, keywords, and titles of the papers were reviewed. Regarding our topic, most relevant papers published between 2007 and 2017 were considered.
Phase 2: We read all the papers filtered in the previous step. Some of the papers were eliminated due to their irrelevant topic. We considered papers that only focus on IoT and RFID adoption in the healthcare domain.
Phase 3: Methodologies and findings of the papers were reviewed. In Sect. 17.3, we give details about the variables which were addressed in these articles.

The number of papers published in journals and conference proceedings is shown in Fig. 17.1. The figure also presents the increasing trend in IoT and RFID adoption in healthcare domain.

17.2.2 Research Framework

In this study, we used a research framework which is presented in Fig. 17.2. First, we address the importance of IoT adoption regarding the perspective of mHealth. Then, we did a literature search in academic databases by using a group of keywords and focus on the articles which mainly investigate IoT and RFID adoption in the healthcare domain. As a result, we summarize main variables which affect adoption decision among different users in terms of top level managers, healthcare professionals, technical staff, and patients. In addition, we present some recommendations for managers to improve the adoption process of IoT devices in their organizations.

17.2.3 Related Work

After the literature search, we found that the number of studies that investigate IoT adoption in healthcare is very limited when compared with the studies which address RFID adoption. The common points of the studies are they mainly

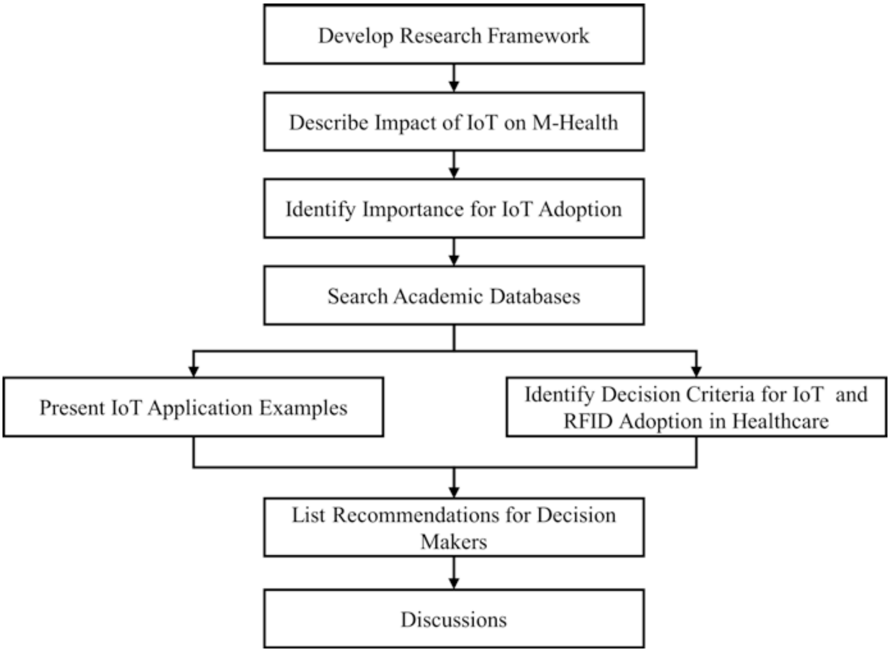

Fig. 17.2 Research methodology

investigate variables that influence adoption of IoT or RFID systems in a healthcare organization and they use surveys to determine these variables. However, these surveys are insufficient to reflect the perceptions of different types of users. In addition, the number of studies that analyze the relation between IoT and mHealth is few. Istepanian et al. (2011), Santos et al. (2014), and Santos et al. (2016) are unique studies that investigate this relation. They propose some theoretical models for integrating IoT capabilities into mHealth applications regarding future Internet. However, technology adoption issues are out of the scope of these studies. It is shown that there is a gap in the literature to analyze the impact of IoT and IoT adoption on mHealth.

In the following sections, we overview the factors that affect IoT adoption and group them regarding stakeholder perspectives. We determine these factors based on previous studies. Since RFID seems as a prerequisite for the IOT domain (Jia et al. 2012), we include the factors that affect both IoT and RFID adoption in healthcare. We mainly use the variables which are discussed in Yazici (2014), Ahmadi et al. (2015), Lai et al. (2014), Fosso Wamba et al. (2013), Yao et al. (2012), and Yao et al.(2010). To support our findings, decision variables described in different application areas by Schmitt et al. (2007) and Wang et al. (2010) are also used in our analysis. In our literature survey, we couldn't find any study that systematically reviews the literature on IoT adoption in healthcare domain.

17.3 Impact of IOT Technologies on mHealth

IoT was initially proposed to refer to interoperable connected devices with RFID technology (Xu et al. 2014). Today, this technology is identified as the Future Internet with the integration into enterprise IT systems (Thoma et al. 2012) and cloud systems. By using IoT technologies, it is possible to collect, record, and analyze data faster and accurate compared to systems that operate individually (Kulkarni and Sathe 2014). Regarding healthcare perspective, IoT technologies can be used for many reasons. Most known application areas of IoT in healthcare can be listed as: patient monitoring and tracking, inventory management, remote surgery, drug distribution, disease diagnosis, patient well-being, and blood bank management (Atzori et al. 2010; Islam et al. 2015; Kang et al. 2013; Kulkarni and Sathe, 2014; Lin et al. 2014; Yu et al. 2012). As an enabling technology, mHealth plays a key role while implementing some of these applications. It behaves as a remote node that provides connectivity with a central location.

mHealth is referred as the implementation of mobile and wireless communication technologies to facilitate and improve healthcare and medical services (Kartsakli et al. 2014). In this study, we use the term "mHealth devices" for mobile phones and medical hubs, "mHealth application" term is used for the applications running on these devices, and "mHealth solution" is used for all type products that include both hardware and software technology for healthcare. Whatever terms are used in the literature, this technology establishes a connection between patients and healthcare professionals and provides remote healthcare delivery by using network technologies. To achieve success, mHealth solutions should be integrated with smart devices in the local environment. At this point, IoT plays a critical role.

IoT provides an architecture to exchange data between mHealth devices and another type of smart devices located in local environments or body area networks. Virtual links between these devices leverage data quality. Ubiquitous healthcare service delivery and service control in a smart environment can be achieved; for example, the health professional verifies the patient and sends a prescription by using smart devices which are interconnected (Santos et al. 2014).

IoT can be also used as a gateway solution rather than an architecture in mobile health scenarios (Santos et al. 2016). The proposed gateway methodology autonomously collects information about the user/patient location, heart rate, and possible fall detection and forwards this information to a caretaker in the real time. The study shows a ubiquitous communication scenario where heterogeneous devices can communicate without human intervention.

As a result, successfully deployed and widely accepted IoT devices ensures mHealth solutions working properly. By the aid of IoT devices and their IP-based connection architecture, mHealth solutions can process critical data in the real time and transmit these data to remote locations for further analysis or diagnosis. Lack of adoption of IoT devices may cause misuse of these devices, and it will decrease the quality of data which is the main source of mHealth applications. In addition, low adoption level of IoT concept also affects the communication between smart systems and mobile devices. Therefore, to utilize the functionalities of mHealth applications, more effort is required to understand decision criteria of IoT adoption.

17.4 IOT and RFID Adoption in Healthcare

17.4.1 Information Technology Adoption in Healthcare

By the increase in Internet and mobile technologies, healthcare service providers can spread healthcare services to anyone, anywhere, and anytime (Lee and Shim 2007). Although a number of smart solutions are introduced for healthcare operations, many of the healthcare professionals do not have enough training and experience on that system (Venkatesh et al. 2011). As a result of lack of training and experience, the adoption rate of these technologies in healthcare takes longer than other application areas (Chong et al. 2012). And, slow adoption may cause healthcare operation failures (Yao et al. 2010). In addition, the effectiveness and efficiency of the healthcare operations would decrease due to the low acceptance rate of these solutions. Therefore, more research is required to understand main variables that influence information technology adoption in healthcare.

There are several models and theories to investigate the adoption of information technologies. Most known theories can be listed as: diffusion of innovation theory, technology acceptance model (TAM), theory of planned theory, theory of planned behavior (TPB), unified theory of acceptance and use of technology (UTAUT), diffusion/implementation model, technology-organization-environment (TOE) framework, social cognitive theory, and task-technology fit chain. They generally explain user or organization acceptance of technologies. In literature, major of studies – including the studies that we surveyed – use these theories to measure and identify the variables in adoption.

There also exist unique studies which use alternative methods to analyze technology adoption factors. For example, Lu et al. (2013) identify adoption factors by using a combination of multiple decision-making models. The study showed that impact of factors may change depending on several parameters such as application area, organization type, or user expectations. Therefore, investigating adoption in a specific technology area would be beneficial to understand unique factors which are specific to the application area. In some cases, a factor (age, gender, etc.) which has a positive impact on the adoption of a system may not influence adoption on another system in a positive way. Therefore, it is critical to analyze the main factors in IoT and RFID adoption in healthcare domain to provide a better understanding of the adoption of these devices. In the following section, we summarized variables which are addressed in previous studies.

17.4.2 Key Factors in IoT Adoption in Healthcare

Technology adoption studies investigate the variables under similar contexts in terms of technology, organization, environment, human, and innovation. Although the contextual approach provides a better understanding of adoption, it may be insufficient to differentiate the expectations of each type of stakeholder who has different education levels, expertise, or needs. We believe that the impact of the variables on adoption would change depending on the type of stakeholder. In the literature Kim and Kim (2016) compared the factors regarding different user views, however, they only present two type of users in terms of patients and non-patients. In our study, we overview the variables regarding four types of users in terms of top level managers, healthcare professionals, technical staffs, and patients. Some of the factors are listed under more than one category, and the impact of the variables on adoption is presented. This categorization shows "Which factors are more important to adopt IoT solutions?" and "Which variables are more important for whom?" The answer to these questions will provide a better understanding of technological adoption, facilitate adoption process, and develop better devices that fit users' expectations.

17.4.2.1 Top Level Manager Perspective

Cost: The financial capability of the organization is a major constraint in the adoption process (Lai et al. 2014). Chong et al. (2012), Dey et al. (2016), Lai et al. (2014), and Lee and Shim (2007) show that most of the decision-makers consider return on investment rather than initial cost. According to Lee and Shim (2007), managers believe that although RFID technologies cost seems high, it would reduce error rates and improve productivity in customer service.

Technological Factors: The technological capability of the organization and complexity of the new system are considered as a critical factor in IoT and RFID adoption in the literature. Chong et al. (2012), Lee and Shim (2007), and Lian et al. (2014) show that decision-makers pay attention to the technical knowledge of their organization in the adoption process. However, Fosso Wamba et al. (2016) and Lai et al. (2014) show that there is not a strong relationship between the complexity of the system and adoption. Lai et al. (2014) support this idea and present that with the assistance of vendors and partners, organizations are able to overcome the technical problems.

Ease of Use: Zailani et al. (2015) showed that perceived ease of use is not significant for managers to adopt radio-frequency identification (RFID).

Competitive Pressure: In previous studies (Cannon et al. 2008; Chong et al. 2012; Reyes et al. 2012; Vijayaraman and Osyk 2006; Zailani et al. 2015), it is proved that competitive pressure has a positive influence on decision-makers to adopt new technologies. According to these studies, top managers believe that technological improvements will improve organizational capability. However, Fosso Wamba et al. (2016) and Lai et al. (2014) show that competitive environment is not significant factors driving RFID adoption among SMEs. Lee and Shim (2007) revealed that competitive pressure has an indirect effect on the likelihood of adopting RFID. Dey et al. (2016) indicate that uncertainty in the healthcare sector is relatively low compared to other sectors, and compelling rules or policies to use RFID technology in health are not clear which may be the reason of low impact of competitive pressure. As a summary, the relation between competitive pressure and adoption may change depending on the firm size or organization type (Cao et al. 2014).

Organization Size: We found that there are contradictory outcomes in the literature about the impact of the organization on adoption. While Brown and Russell (2007), Iacovou et al. (1995), Lai et al. (2014), and Reyes et al. (2016) show that larger firms are more likely to be associated with a higher adoption stage. Chong and Chan (2012) present that there is not a strong relationship between organization size and adoption. Regarding these results, it is required to consider organization type rather than organization size for predicting and defining the steps of IoT adoption in healthcare.

Managerial Characteristics: Fosso Wamba et al. (2016) prove that education level, gender, and age of managers have a strong influence on the technology adoption process. Although Venkatesh et al. (2014) suggested that younger managers who have higher education are more open to taking the risk for new technologies, Fosso Wamba et al. (2016) found that older managers were more likely to adopt RFID technologies. Van Slyke et al. (2002) investigated the impact of gender for online shopping and found that men are more likely to buy products or services online than women. However, Fosso Wamba et al. (2016) cannot prove the positive impact of male managers on adoption. We believe that more research is required to analyze the impact of age, gender, and education level of managers on adoption in detail.

The Geographic Location of Organization: Fosso Wamba et al. (2016) present that geographic location of the organization has an influence on the adoption of technologies. According to the study, organizations which are located close to metropolitan areas are more likely to adopt RFID technology.

Business Sector: Fosso Wamba et al. (2016) found that type of business sector was not significant on adoption. However, most of the organizations sampled in that study perform in service sector and manufacturing. None of them is healthcare organizations, and therefore the impact of the business sector on adoption cannot be proved.

Country of Business: Fosso Wamba et al. (2016) found that developed countries have positive intention to adopt RFID systems. In our study, we could not find any study that compares the RFID and IoT adoption level between the same types of companies originated in different countries.

Relative Advantage: Perceived relative advantage does not have a direct impact on intention to adopt RFID technologies. Although Zailani et al. (2015) show a weak relation between relative advantage and adoption, Lai et al. (2014) and Lee and Shim (2007) couldn't show the relative advantage as a strong variable on adoption.

Security and Privacy: Zailani et al. (2015) show that security and privacy concerns are significant predictors of hospital managers' intention to adopt RFID technology. If the system has a secure architecture, managers are likely to adopt the system.

Policies and Government Support: Lee and Shim (2007) and Zailani et al. (2015) show that government policy concerns are significant predictors of hospital managers' intention to adopt RFID technology. Kuo and Chen (2008) depict government support as an important trigger for success in RFID deployment projects. Therefore, policies and government support seem as strong motivators in IoT adoption.

17.4.2.2 Healthcare Professionals' Perspective

Perceived Usefulness: Perceived usefulness is an important driver of intention to adopt RFID among healthcare professionals (Zailani et al. 2015). However, more functionality does not mean much usefulness since high automation and elimination of human intervention would bring some risks to users (Cocosila and Archer 2010). Therefore, it is required to balance the level of automation and functionality in the design phase.

Perceived Ease of Use: According to Unnithan et al. (2013) and Zailani et al. (2015), perceived ease of use has a positive impact on RFID adoption among healthcare professionals. The learning curve of the products is also another important issue which affects adoption of the systems (Bellagente et al. 2016).

Education: Abdulaziz et al. (2017) show that main reasons for dissatisfaction were found to be inadequate training and computer skills. They present that technology satisfaction level is higher among nurses who have advanced computer skills.

Security and Privacy: Recent studies show that healthcare professionals allowed the collection of information on the condition that the confidentiality of these data was not infringed. Therefore, security and privacy can be considered as significant factors that influence the intention of technology adoption (Holzinger et al. 2008; Zailani et al. 2015; Khoumbati et al. 2010).

Top Management Support: Top management support has the most significant influence on adoption. Jeyaraj et al. (2006), Dey et al. (2016), Lee and Shim (2007), Reyes et al. (2016), Thong and Yap (1995), and Thong (1999) show the positive influence of top management support in RFID and IoT adoption.

Design: Design parameters can be listed as resistance to environmental conditions, size, transmission jittering, and battery life. The impact of these factors is investigated by Cao et al. (2014). According to the study, well-designed products are adopted easier than other products by the users.

Social Persuasion: Singh et al. (2015) propose that social persuasion has a great impact on technological trends such as IoT and mobile devices.

17.4.2.3 Patients' Perspective

Security and Privacy: Security and privacy are significant factors in adoption (Chong and Chan 2012; Fosso Wamba et al. 2016; Wamba and Ngai 2011). Patients generally do not intend to transmit their personal data over automated systems due to security and privacy considerations. Therefore, security and privacy should be addressed while storing and transmitting individuals' data. Henze et al. (2016) ensure an integrated solution for privacy enforcements for cloud-based IoT concepts. It is proposed that individual end users and developers are regarded at the same time. As a result, it is obvious that there is a need for more work to find out appropriate ways to process personal data in public environment.

Relative Advantage: Relative advantage is one of the important determinants of technology adoption in the user perspective (Rogers 1995). Similarly the RFID and IoT domain, relative advantage is also an important factor (Fosso Wamba et al. 2016), and it has a positive influence on the adoption process.

Word of Mouth: Word-of-mouth and user-generated content are important factors among the end users. Mital et al. (2017) and Roy et al. (2016) propose these variables as a great motivator on the adoption of IoT devices especially among users who have low income.

Gender and Age: Both gender and age are strong predictors in technology adoption (Venkatesh et al. 2014; Yee-Loong Chong et al. 2015). According to these studies, younger users are more likely to adopt technologies than older ones. However, these studies address general technology adoption rather than IoT concept. In our literature survey, we couldn't find any study that investigates the impact of age and gender on the IoT adoption among patients.

Ease of Use and Education: Thaduangta et al. (2016) showed that difficulty of the system and lack of education influence perceived usefulness of the system negatively, and users feel nervous while using the technology. Benoît et al. (2009) found that learning has a positive impact on adoption and provides positive emotions against the technology. Therefore, education seems a strong motivator on adoption.

17.4.2.4 Technical Staff Perspective

Technological Limitations: Technical capabilities and use of common standards are considered as determinants in the technical perspective (Wamba and Ngai 2011; Dey et al. 2016). Lack of technical capabilities and interference with other devices are considered as important barriers to use the RFID and IoT solutions (Lin et al. 2014; Pustiek et al. 2016).

Compatibility Factors: Chong and Chan (2012) found that there is no significant relationship between compatibility and adoption. However, researchers state that compatibility of the system is significant in routinization stage that fully integrates new systems with existing ones after the adoption process. On the other hand, Cao et al. (2014), Dey et al. (2016), Fosso Wamba et al. (2016), and Lai et al. (2014) show that compatibility between new systems and existing devices is important for technical staff. Technicians and IT managers are likely to use new devices if the devices are compatible with the existing systems. In addition, it is proposed that perceived complexity of the systems can be reduced (Chong and Chan, 2012). The flexibility of the technical infrastructure is another determinant if the IT infrastructure of an organization is flexible enough to implement new technologies (Dey et al. 2016).

Table 17.2 Research methodology

Parameter	Variable	Top level managers	Healthcare professionals	Patients	Technical staff
Higher	Cost	N			
	Return on investment	+			
	Technical knowledge	+/N			
	Security and privacy	+	+	+	+/N
	Relative advantage	+/N	+	+	
	Perceived usefulness				
	Ease of use	N	+	+	
	(Lower) Learning curve				
	Competitive pressure	+/N			
	Strict policies and government support	+			
	Organization size	+/N			
	Elimination of human intervention		–		
	Top management support		+		
	Social persuasion		+	+	
	Word of mouth				
	Compatibility				+/N
	Education level		+		
Older	Age	+/–		NMR	
Male	Gender	+			
Closer to metropolitan cities	Geographic location of organization	+			
–	Business sector	NMR			
Developed	Country	+			
Better	Design		+		+
	Technical capability				

+ Positive effect, – negative effect, N no strong relationship, +/N studies are existed show either positive effect or no strong relationship, NMR need more research

Security and Privacy: Privacy and security were rated some of the least concerning aspect by technical staff in RFID adoption (Dey et al. 2016). This is contradictory with previous findings presented in Lai et al. (2014) and Tsu Wei et al. (2009).

Regarding the findings in previous studies, we summarize the variables in Table 17.2. Some of the variables are aggregated under a single term since some studies may refer same concepts by using different terms. "+" shows the variables which have a positive effect on adoption, whereas "–" shows the variables that have a negative effect. "N" depicts the variables which do not have a strong relationship with adoption. "NMR" presents variables which have been addressed but needs more research for detailed analysis. Blank cells show the variables have not been investigated in the studies that we surveyed. These variables and different perspectives are illustrated in Fig. 17.3.

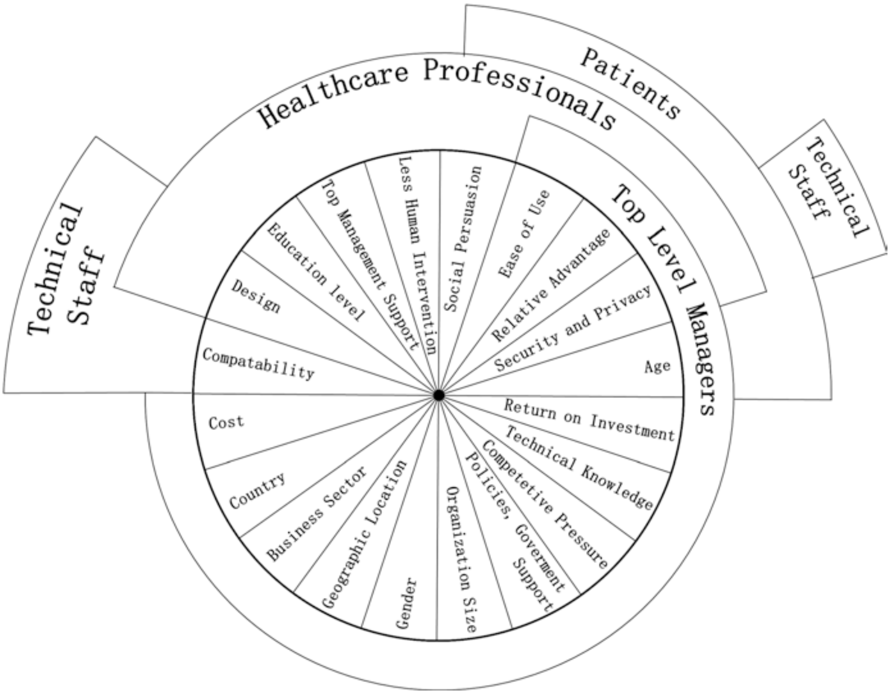

Fig. 17.3 User perspective adoption chart

17.5 Recommendations for Healthcare Organizations and Service Providers

Managers and IT staff of the healthcare organizations need to follow predefined instructions to achieve success in IoT adoption. To address this requirement, we propose the following recommendations to ensure wide adoption of IoT solutions among patients and healthcare professionals. Widely adopted IoT solutions would enable using more mHealth devices in healthcare organizations. In such perspective, these recommendations directly influence the use of m-Heath implementations.

17.5.1 Inform Users

The gap between expectations and actual results has a negative impact on organizational level RFID adoption (Kuo and Chen 2008). If the user perceives that the new system does not satisfy his/her needs, he/she may not adopt and use it. Therefore, organizing events to educate users and using social media platforms and discussion forums would leverage adoption level of the users (Alaiad and Zhou 2017; Unnithan et al. 2013). Informed users will be more motivated to use IoT technologies, which will directly lead to increased use of mHealth solutions in enterprises.

17.5.2 Customize Technology

We believe that there is no a technological solution that fits all cases; in other terms, there is no "silver bullet." "Customization" is a strong motivator in adoption (Unnithan et al. 2013). Therefore, customization of the technology is needed to address actual needs of the organization. Users willingly use the systems when they see that the system has capabilities to accomplish their needs. Such a user motivation will lead to use IoT solutions in corporations. In addition, customization is useful in solving compatibility issues that may arise between IoT solutions and mHealth implementations. Systems that integrate with each other will increase the productivity and efficiency of information systems of organizations.

17.5.3 Listen Users

Previous studies showed that major reasons for IT failures are inadequate understanding of the users' expectations and preferences. Since the only way to succeed in IoT and RFID adoption in healthcare can be listed as considering users' needs, developing user-specific devices, and improving the products based on user feedbacks even after product release. Therefore, developers should pay attention to user needs. Interviews and surveys are the easiest methods to elicit the user requirements. In addition, to identify user needs, previous experiences in mHealth implementations can be also used. User feedbacks on mHealth technologies will contribute to the identification of requirements and development of new IoT solutions.

17.5.4 Ensure Privacy

As shown in the previous sections, security and privacy are the main considerations for all types of users. Developers and organizations should ensure the privacy of individuals' personal information to convince users to use the product. Privacy can be ensured by using two methods (Cicibaş and Demir 2016). In the first method, users set the permissions in their IoT devices by using a privacy language which is similar with a method presented for smartphones (Vincent et al. 2011). In the second method, users are informed about data collection with a message indicating that it is to serve business needs. We believe that the first method is more applicable since users are more familiar with the method which is used in mobile solutions. Current solutions that address mHealth privacy will also meet the privacy issue of IoT solutions.

17.5.5 Use Social Hubs

In organizations, there are popular employees who have an influence on other employees. They can persuade others toward a particular belief (Demir and Ozkan 2015). Managers are also a type of such employees. Organizations should convince these members first and then support them to spread their beliefs to other employees. Therefore, adoption decision can be diffused to other members easily. Similarly, social influence is proved as a strong motivator in mHealth adoption (Sun et al. 2013; Kwon et al. 2016). Although users generally make decisions based on their own evaluations, they are affected by social influence while adopting mHealth technologies (Sun et al. 2013).

17.6 Conclusion

IoT provides an architecture to exchange data between mHealth devices and another type of smart devices which are located in the environment. Virtual links between these devices leverage data quality and improve the efficiency and effectiveness of these devices. Moreover, IoT architecture provides processing data which are collected by different types of mobile devices such as mobile phones, implantable sensors, wearable devices, and ambient-assisted living solutions. Regarding these functionalities, IoT plays a key role in the mHealth domain.

In our study, we investigated adoption variables of IoT in healthcare domain and then summarized these variables regarding perspectives of different types of users. In addition, we listed several actions that could be taken by organizations to leverage the effectiveness of IoT implementations in hospitals or other healthcare organizations.

We found that there is a gap in the literature to explain the adoption of healthcare applications by specifically addressing the unique characteristics of IoT technology. Most of the studies investigate adoption factors in IoT healthcare applications by using the results which are taken in a specific period of time (Kim and Kim 2016). However, it is required to observe long-term perceptions of the users to understand the actual adoption of IoT devices.

As a result, to leverage the effective use of mHealth technologies in multi-technological environments, more research is required. Further studies should analyze the role of IoT in healthcare in detail. We believe that IoT will assist widely deployment of mHealth applications in healthcare. In addition, increasing demand of patients, home-based healthcare needs, and the growth of smart objects will also launch new mobile health applications (Cloudmine Inc. 2016).

Mobile health applications should be shaped regarding the concepts of IoT. During this transformation, we need to talk about mobile-enabled health applications rather than mobile health applications. New services and business models can succeed by using such a consortium.

Acknowledgments The views and conclusions contained herein are those of the authors and should not be interpreted as necessarily representing the official policies or endorsements, either expressed or implied, of any affiliated organization or government.

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E. Sezgin et al. (eds.), *Current and Emerging mHealth Technologies*,
https://doi.org/10.1007/978-3-319-73135-3