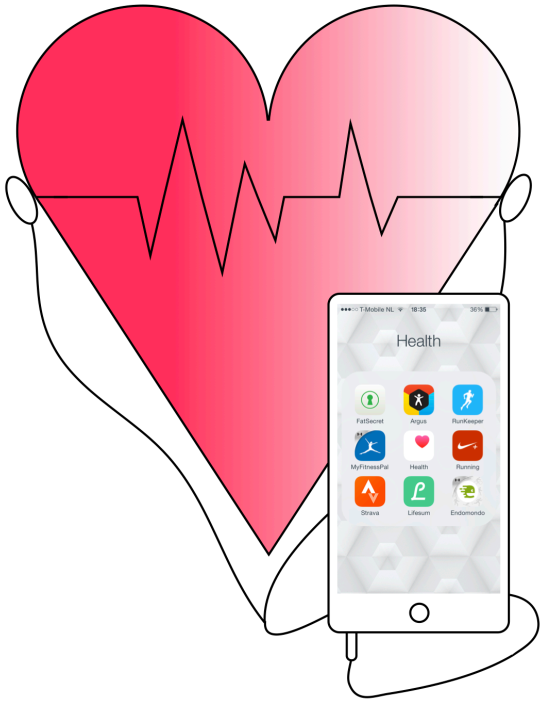
Healthcare Anytime Anywhere

A Case Study About the Factors Predicting Initial and Continuous Usage Intention of Health-related Smartphone Applications among Dutch Users



UNIVERSITY OF TWENTE. Master Thesis | Carolyn Krogoll

Detailed Information

Institute

University of Twente
Drienerlolaan 5
7522 NB Enschede

Faculty and Program

Faculty of Behavioral Sciences
MSc Communication Studies
Marketing Communication and Consumer Behavior

Graduation Committee

Dr. A. D. Beldad
Dr. S. A. de Vries

Author

Carolyn Krogoll
s1492772

Date

29.05.2015

Abstract

Objective:
The healthcare industry is undergoing profound changes resulting from advancements in mobile technology. With promising innovations like mobile health applications or wearable health devices such as the Apple Watch or the Microsoft Fitness Band, consumers are being encouraged to manage their health more independently. Especially health-related smartphone applications hold great potential for improving public health as they offer access to healthcare anytime anywhere. However, little is known about how to achieve effective user adoption. Understanding users' initial and continuous usage intention of health-related smartphone applications is therefore essential for the success of future mobile health services.

Design & Methods:
The proposed research model is based on the Extended Unified Theory of Acceptance and Use of Technology (UTAUT 2). It was predicted that performance expectancy, effort expectancy, social influence, facilitating conditions, hedonic motivation, and price value positively affect initial usage intention, while habit replaces price value for continuous usage intention of health-related smartphone applications. The research model was completed with additional factors relevant for health app usage. Usage intentions were therefore predicted to also depend on consumers' trust in the app provider, the perceived privacy risks, and consumers' valuation of health. The latter one was also predicted to indirectly affect usage intention through performance expectancy. A one-shot online questionnaire was carried out in the Netherlands to test the proposed hypotheses. To investigate the factors predicting initial and continuous usage intention respectively, participants were split into non-users (N = 160) and users (N = 213) of a health-related smartphone application.

Results & Conclusions:
Results of hierarchical regression analyses reveal that initial usage intention of health-related smartphone applications is determined by performance expectancy, hedonic motivation, the social influence of friends and relatives, as well as by consumers' trust in the in the app provider; while continuous usage intention is exclusively determined by habit. It was further detected that consumers' valuation of health has an indirect positive effect on both, initial and continuous usage intention through performance expectancy. Furthermore, results of simple linear regression analyses reveal that trust in the app provider has a significant impact on users' perceived privacy risks of their most used health app. The results of this study add theoretical knowledge to the field of consumer health technology and give app providers and healthcare practitioners ideas for marketing their services to the Dutch consumers.

Keywords: health-related smartphone applications, mobile health, public health, UTAUT 2

Acknowledgements

I am very appreciative to have been given the opportunity to conduct research in my area of interest. Mobile health is just at the beginning of transforming the healthcare industry and I am excited to have been part of its very first investigations.

Nevertheless, this paper should not be credited to me only, as it is the result of many great people working together. I would like to take this opportunity and thank those, who have supported me the most throughout this period.

First and foremost, I would like to thank my supervisors Ardion Beldad and Sjoerd de Vries for their valuable observations and knowledge sharing. It was an experience full of inquisitiveness, encouragement, and stimulation – I enjoyed working with you. Secondly, I would like to express my gratitude to my family, friends, and partner for giving me comfort and reassurance. Special thanks go to my mother for her unconditional love and believing in me no matter what.

Enschede, May 2015

Carolyn Krogoll

Table of Contents

List of Figures

List of Tables

1. Introduction

Over the last years the use of mobile devices has become ubiquitous around the world (Klasnja & Pratt, 2012; Patrick, Griswold, Raab & Intille, 2008; Van Velsen, Beaujean & Van Gemert-Pijnen, 2013; West, 2012). Technological advancements have transformed the lives of many including consumers, businesses, and entire segments of society (West, 2012). Sectors such as education and finance have undergone profound changes due to innovations in mobile technology (Boulos, Wheeler, Tavares & Jones, 2011; Meulendijk, Meulendijks, Jansen, Numans & Spruit, 2014; Wang, Park, Chung & Choi, 2014).

A major industry that is currently experiencing these technical developments is the healthcare sector. With the introduction of mobile health applications for smartphones, tablets and supplementary wearables such as smart watches, activity trackers, or fitness bands, the healthcare industry is transforming towards a more patient-centered care (Lober & Flowers, 2011). Persons being treated for health reasons are no longer merely patients, but have become consumers who demand to take control of their own health. Mobile health is therefore a groundbreaking opportunity for public health, as it sets new paradigms in which healthier living and ageing are facilitated (PwC, 2013). Considering that Europe is facing drastic health care costs due to the treatment of chronic diseases and ageing populations (PwC, 2012[b)]), mobile health services hold great potential: Due to their immediacy and the widespread availability, mobile devices can empower large segments of consumers to manage their health more independently, raise awareness of the importance of healthy lifestyles and achieve behavioral change while reducing health care costs (Avancha, Baxi & Kotz 2012; Bender et al., 2014; Funk, 2013; PwC, 2013; Simons, Hampe & Guldemond, 2013).

At this moment, smartphones are the most important mobile device for realizing health-related behavior thanks to their unique position in the mobile market (research2guidance, 2014). With health-related smartphone applications (from now on referred to as apps) such as activity trackers, calorie counters or sleep cycle analyzers, consumers can access healthcare anytime, anywhere. Yet, despite their potential of facilitating positive socio-demographic impacts, health-related smartphone apps face a slow user adoption (Ariaeinejad & Archer, 2014; Dehzad, Hilhorst, De Bie & Claassen, 2014; Funk, 2013; PwC, 2013). The overwhelmingly wide choice of apps (Van Velsen et al., 2013) as well as lacking data security (Albrecht, Pramann & Von Jan, 2014; Dehzad et al., 2014; Meulendijk et al., 2014; West, 2012) are two major barriers that justify why such health services are limited in tapping their full potentials. On the one hand, it is difficult for consumers to distinguish between good and poor quality apps, let alone to know determinants of a good quality health app (Su, 2014; Van Velsen et al., 2013). Recent studies reveal that consumers can find almost 100.000 different health-related apps (Dehzad et al., 2014; research2guidance, 2014). On the other hand, consumers are worried about the possible maltreatment of their personal health data (Albrecht et al., 2014; Avancha et al., 2012; Funk, 2013; Dehzad et al., 2014; Meulendijk et al., 2014; PwC, 2012[a)b)]; Van Velsen et al., 2013; West, 2012). As health-related apps have primarily emerged outside the traditional healthcare system (Funk, 2013), lacking regulatory frameworks for security and data protection present another obstacle for health app user adoption (Albrecht et al., 2014; Funk, 2013; PwC, 2012[a)b)]; research2guidance, 2014). Consequently, health-related app providers encounter issues in adequately targeting their product to the end-users (resarch2guidance, 2014). The question is, *what drives consumers' initial usage intention with regards to health-related smartphone apps?* And most importantly, as the excitement usually decreases following initial adoption of information technologies (Geiselhart, 2015), *what influences their continuous usage intention?* The objective of this study is therefore to determine which factors predict consumers' initial usage intention of health-related smartphone apps, and which factors influence continuous usage intention for those who have already adopted them.

The study proposes a research model based on the Extended Unified Theory of Acceptance and Use of Technology (UTAUT 2). It is predicted that factors such as performance expectancy, effort expectancy, social influence, facilitating conditions, hedonic motivation, price value, and habit (Venkatesh, Thong & Xu, 2012) will positively affect usage intentions of health-related smartphone apps. Furthermore, the model is adjusted with additional factors relevant for health app usage: That is, trust in the app provider, the perceived privacy risks of using the health-related smartphone app, and consumers' valuation of health are further determinants presumed to affect usage intention. It is also predicted that consumers' valuation of health indirectly affects usage intention through performance expectancy.

As the medical field is presumed to profit tremendously from mobile health solutions in the future (research2guidance, 2014), this study aims to contribute theoretical knowledge in the domain of consumer health technology. Because the Netherlands is a leading country in smartphone adoption within the EU (Hofstede, 2013; Oosterveer, 2013; Otto, 2014), it offers a promising market for the mobile health industry (research2guidance, 2015). This is why the Dutch market has been chosen to function as a case study for this research. Ultimately, results of this study will give app providers and healthcare practitioners ideas for targeting their services successfully to the Dutch market.

In the next chapters the potential of health-related smartphone apps as new health agents will be explained together with a brief description of their characteristics. Subsequently, the research model, including hypotheses development for the initial and continuous usage intention of health-related smartphone apps will be presented. The method section will explain the procedural steps taken. Based on the research results, the paper will conclude with theoretical and practical implications. Finally, directions for future research will be given.

2. Theoretical Framework

Before addressing the theoretical elements for explaining initial and continuous usage intention of health-related smartphone apps, the unique value of the smartphone as a medium as well as its potential to provide health services need to be acknowledged. The following sections will briefly refer to that matter, and explain how a health-related smartphone app can be used as a tool for supporting health behavior. Subsequently, the difference between a medical and a health-related smartphone app will be clarified, and the significance of the latter emphasized.

2.1. Anytime Anywhere Thanks to the Smartphone

Through the advancements of information technologies mobile phones are no longer limited to services such as calling, text messaging, or taking pictures (Boulos et al., 2011). With computer qualities (Boulos et al., 2011; Handel, 2011; Kim, Yoon & Han, 2014; Verkasalo, López-Nicolás, Molina-Castillo & Bouwman, 2010), these devices offer smart features including refined graphical interfaces with touchscreen display and the ability to access the Internet due to wireless services such as Wi-Fi, 3G, or 4G. (Boulos et al., 2011; Kim et al., 2014; Mroz, 2013). For the most part however, smartphones have attained their unique position within the mobile market (Funk, 2013) due to the novelty of installing apps (Mroz, 2013), which are programs that can be downloaded from the app store of the user's smartphone operating system. Developed to provide the user with specific functions (Handel, 2011), apps are experienced as a crucial added value in smartphone usage, which explains the central position of smartphones in the every day life of today's consumers (Funk, 2013; Mroz, 2013). About three billions app-downloads were carried out within one year since the introduction of apps in 2008. By 2012, this number increased fifteen-fold representing a total of 45 billion app downloads (Mroz, 2013). Not surprisingly, the mobile app market has been defined as one of the fasted growing industries today (App Annie, 2015; research2guidance, 2014).

2.2. Smartphone Apps as New Health Agents

There are various kinds of apps, usually distinguished in categories within the app stores (Mroz, 2013). Android and iOS dominate the app market compared to other mobile operating systems, resulting in a similar leading share in smartphone health apps (research2guidance, 2014). The Google Play store and the Apple app store distinguish health apps between the categories 'Health and Fitness' and 'Medical'. However, as app providers have the possibility to submit their app to more than one category, one might not find such a clear distinction in the app stores (App Annie, 2015; Mroz, 2013). Also, health-related smartphone apps have been primarily developed without the involvement of healthcare institutions (Funk, 2013), which makes it is difficult to specify the crossing line between 'Health and Fitness' and

'Medical'. Generally speaking, apps from the category 'Health and Fitness' are directed at consumers and include anything from a calorie counter and activity tracker to a meditation device or sleep cycle analyzer (Harpham, 2015; Mroz, 2013). Such health-related smartphone apps offer a variety of functions that support consumers in making healthy lifestyle choices. In contrast, 'Medical' apps are primarily addressed to medical audiences such as physicians or medical students (Mroz, 2013) amongst others to assist them in medical decision-making; but also to assist patients in managing diseases (Harpham, 2015). Hence, their focus lies on supporting the diagnosis, treatment, and monitoring of one or more diseases such as diabetes or obesity (PwC, 2012[b)]; research2guidance, 2014). The key difference between a medical and a health-related smartphone app therefore lies in the methodological approach of its data collection and usage (Harpham, 2015).

At the moment, medical apps are still in its fits and starts, and clearly outnumbered by health-related apps (research2guidance, 2014). In a recent study, Funk (2013) detected that almost 70% of all examined health apps have been designed to support consumers in the prevention of diseases, compared to less than 6% medical apps intended to support disease management. This is not surprising considering their enormous potential of improving public health (PwC, 2013; research2guidance, 2014). Health-related smartphone apps have the ability to reduce the threat of chronic diseases "by 50-73%, depending on the type of disease" (PwC, 2013, p.4).

Figure 1 depicts a selection of the most popular health-related smartphone apps from the category 'Health and Fitness' of Apple's app store and the Google Play store in the Netherlands.

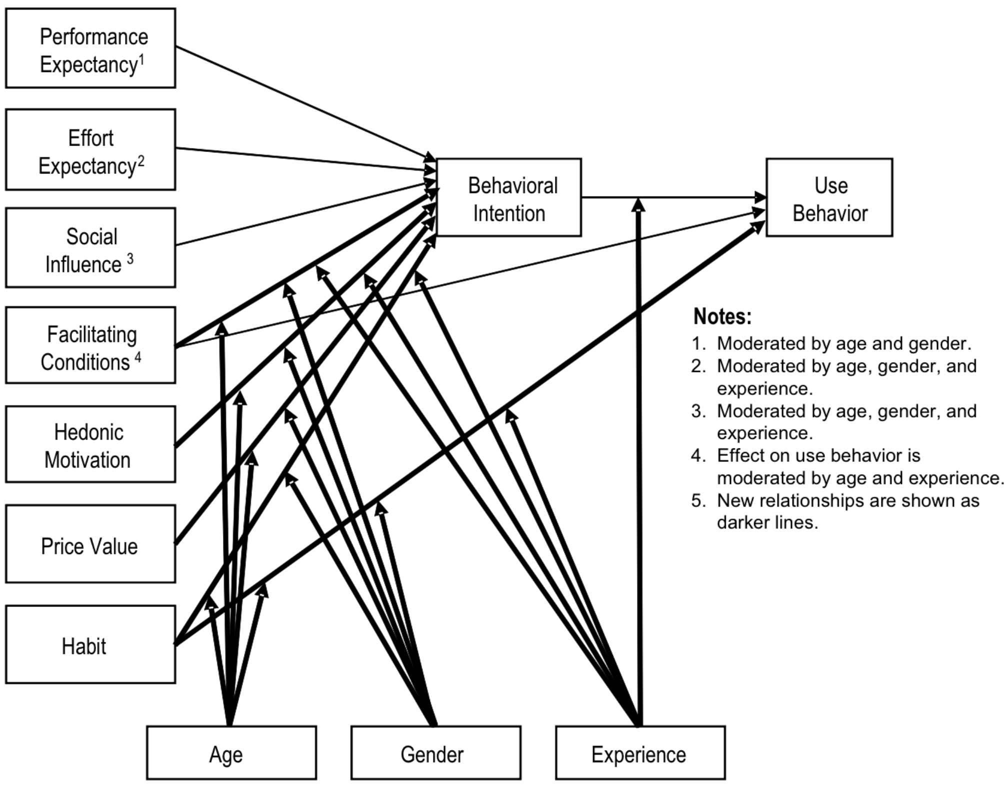
Figure 1

Selection of popular health-related smartphone apps from the Apple- and Google Play store in the Netherlands

2.3. Investigating Initial and Continuous Usage Intention

Studies investigating technology acceptance and usage are not a new phenomenon and crucial for predicting user adoption (Wilkowska & Ziefle, 2011). Due to increasing consumer empowerment and the high penetration of mobile technologies (Ariaeinejad & Archer, 2014), the Extended Unified Theory of Acceptance and Use of Technology (UTAUT 2) has been proposed to explain technology use and acceptance within the consumer context (Venkatesh et al., 2012). It builds on its precursor the UTAUT - suggested for investigating the professional context (Venkatesh et al., 2003), and captures all essential elements and relationships of the eight most recognized technology acceptance models (i.e. Technology Acceptance Model (TAM), Theory of Reasoned Action (TRA), Motivation Model (MM), Theory of Planned Behavior (TPB), Innovation Diffusion Theory (IDT), Social Cognitive Theory (SCT), Model of PC Utilization (MPCU), Combined TAM and TPB (C-TAM-TPB) (Venkatesh et al., 2012). The UTAUT 2 has been successfully applied to a diversity of fields, including mobile banking (Yu, 212; Zhou, Lu & Wang, 2010), education (Raman & Don, 2013), e-commerce (Escobar-Rodriguez & Carvajal-Trujillo, 2014), and most recently to healthcare (Ariaeinejad & Archer, 2014; Slade, Williams & Dwivedi, 2013). Thus, using the UTAUT 2 as a basis for predicting initial and continuous usage intention of health-related smartphone apps seems justified. Figure 2 depicts the original UTAUT 2 proposed by Venkatesh et al. (2012).

Figure 2
The UTAUT 2 model (Venkatesh et al., 2012)



The model builds on four core constructs (i.e. performance expectancy, effort expectancy, social influence, and facilitating conditions) and adds three more consumer relevant factors (i.e. hedonic motivation, price value, and habit).

2.3.1. Performance Expectancy

Performance expectancy has been found to be the strongest predictor of intention to use technology among studies related and unrelated to the consumer health context (Ariaeinejad & Archer, 2014; Escobar-Rodriguez & Carvajal-Trujillo, 2014; Kijsanayotin et al., 2009; Or et al., 2010; Raman & Don, 2013; Venkatesh et al., 2012; Yu, C., 2012; Zhou et al., 2010). Based on the definition by Venkatesh et al. (2012), performance expectancy refers to "the degree to which using a technology will provide benefits to consumers in performing certain activities" (p.159) and therefore reflects elements of utilitarian value (extrinsic motivation) such as perceived usefulness and outcome expectations (Venkatesh et al., 2003). Within the context of this study, performance expectancy defines the health benefits that consumers can achieve from using a health-related smartphone app. This thought has been derived from theoretical notions of the Health Belief Model (HBM) as well as The Protection Motivation Theory (PMT). While PMT suggests intentionally engaging in health-related behavior due to fear of experiencing serious diseases (Milne, Sheeran & Orbell, 2000; Milne, Orbell & Sheeran, 2002; Sun, Wang, Guo & Peng, 2013), HBM similarly implies that "following a particular health recommendation would be beneficial in reducing the perceived threat" (Rosenstock, Strecher & Becker, 1988, p.177). Several researchers have used these theories to predict patient and consumer health behaviors (Janz & Becker, 1984; Milne et al., 2000; Milne et al., 2002; Rosenstock et al., 1988; Schwarzer, 2008; Smith & Stasson, 2000; Sun et al., 2013). It can be assumed that initial and continuous usage intention of health-related smartphone apps rises once a consumer recognizes their healthcare benefits. Therefore, the first hypothesis is formulated as follows:

Hypothesis 1[a)]

Performance expectancy positively affects initial and continuous usage intention of health-related smartphone apps.

[a)] non-users and user

2.3.2. Effort Expectancy

Effort expectancy implies the ease of using a technology (Venkatesh et al., 2012). With the increasing advancements of smartphones, the utilization of high-tech features that come along with it will progress only further in the future. Graphic interfaces, touchscreen display, and size of the touch pad are amongst others important elements that influence the ease of use experienced by the consumer (Mroz, 2013). In the context of this study, effort expectancy means the ease associated with using a health-related smartphone app and is therefore, important for initial as well as continuous usage intention. Various studies have shown that effort expectancy is an important determinant of user adoption and usage behavior (Ariaeinejad & Archer, 2014; Escobar-Rodriguez & Carvajal-Trujillo, 2014; Kijsanayotin et al., 2009; Or et al., 2010; Raman & Don, 2013; Venkatesh et al., 2012). It can be argued that easily learning how to use a health-related smartphone app; clear and understandable interaction with the app; and its overall ease of use will increase the likelihood of usage intention. In fact, mobile health experts agree that in order for such services to be consumer-friendly, they need to manifest certain standards (PwC, 2013; research2guidance, 2014). This means, not only do health-related smartphone apps need to match the technical understanding of the user, but also be in line with the user's health literacy. If this cannot be achieved the ease of using a health-related smartphone app will be negatively impacted (PwC, 2013). Hence, it is hypothesized:

Hypothesis 2[a)]
Effort expectancy positively affects initial and continuous usage intention of health-related smartphone apps.
[a)] non-users and user

2.3.3. Social Influence

Social influence has been proven to be a significant predictor for the acceptance and use of technologies within different contexts (Venkatesh et al., 2012), including health care (Ariainejad & Archer, 2014; El-Wajeeh, Galal-Edeen & Mokhtar, 2014; Kijsanayotin et al., 2009; Or et al., 2010), mobile banking (Yu, 2012; Zhou et al., 2010), education (Raman & Don, 2013), and as e-commerce (Escobar-Rodriguez & Carvajal-Trujillo, 2014). However, depending on the situation, social influence has not always shown consistent impacts (e.g. Escobar-Rodriguez & Carvajal-Trujillo, 2014; Or et al., 2010). Too often, authors have not clearly defined the construct so that it could not be adequately operationalized (Holden & Karsh, 2010). For instance, social influence has primarily been defined and limited to “important others” (e.g. Venkatesh et al., 2012, p.159), regardless of the research context.

To conform to the present research context, social influence has been defined based on the different sources of social influence relevant for health app usage (Holden & Karsh, 2010). Firstly, it is argued that the social influence from friends and relatives will have a positive impact on the initial and continuous usage intention (e.g. Cheng, Mendonca & De Farias Júnior, 2014; El-Wajeeh et al., 2014; Muzaffar, Chapman-Novakofski, Castelli & Scherer, 2014; Weber, Martin & Corrigan, 2007). Theoretical notions of social influence are based on subjective norm from the Theory of Reasoned Action (TRA) and Planned Behavior (TPB). It refers to “the perceived social pressure to perform or not to perform the behavior” (Ajzen, 1991, p.188), and thus, friends, parents and other family members become important influencers for the intention to engage in health-related behavior (Finlay, Trafimow & Jones, 1997; Gass & Seiter, 2014). Secondly, as the integration of health apps to the clinical workflow of medical practitioners, pharmacies, and other health-related institutions is foreseen to positively impact adoption barriers (Funk, 2013), it can be argued that healthcare specialists exert an influence consumers' initial and continuous usage intention as well. In fact, in a study conducted by Funk (2013) participants perceived their physician as a credible source for health app usage recommendations. Correspondingly, a study conducted by PricewaterhouseCoopers (2012[b)]) reveals that cooperation between app developers and major healthcare providers would make consumers more comfortable in adopting mobile health services. For this study, social influence therefore has been defined as the extent to which consumers perceive that (1) friends and relatives, as well as (2) healthcare specialists believe they should use a health-related smartphone app. The following is hypothesized:

Hypothesis 3.1[a)]
Social influence exerted by friends and relatives positively affects initial and continuous usage intention of health-related smartphone apps.
[a)] non-users and user

Hypothesis 3.2[a)]
Social influence exerted by healthcare specialists positively affects initial and continuous usage intention of health-related smartphone apps.
[a)] non-users and user

2.3.4. Facilitating Conditions

Facilitating conditions "refer to consumers' perceptions of the resources and support available to perform a behavior" (Venkatesh et al., 2012, p.159). The construct is known to be a significant predictor of user adoption and usage behavior in a wide scope of research, including healthcare (Ariaeinejad & Archer, 2014; Escobar-Rodriguez & Carvajal-Trujillo, 2014; Or et al., 2010; Zhou et al., 2010). Within the context of this study, it is suggested that facilitating conditions present the resources and support available to consumers when using a health-related smartphone app. These can include almost anything, varying "significantly across application vendors, technology generation, [and] mobile devices […]" (Venkatesh et al., 2012, p.162). For instance, the conditions whether a consumer's smartphone operates on Wi-Fi, 3G or 4G will influence the speed of data transfer (Mroz, 2013) and, therefore, how well the app functions. Furthermore, facilitating conditions may depend on several features, including the type of smartphone (e.g. iPhone or Samsung); the operating systems it works on (e.g. iOS or Android); the size of the display and its graphical features (small vs. big and low quality vs. high quality); in how far the health app is compatible with other technologies the consumer uses (i.e. wearables such as smart watches, fitness bands, or other apps); the knowledge the consumer possesses to use such an app; and the help available once the consumer has trouble using the app. It can be argued that a good amount of resources has a positive effect on initial and continuous usage intention of a health-related smartphone app. (Venkatesh et al., 2012). Hence, the following is hypothesized:

Hypothesis 4[a)]
Facilitating conditions positively affect initial and continuous usage intention of health-related smartphone apps.
[a)] non-users and user

2.3.5. Hedonic Motivation

As one of the first three added factors to the original UTAUT, hedonic motivation is "defined as the fun or pleasure derived from using a technology" (Venkatesh et al., 2012, p.161). Integrating this construct from the motivation theory, it complements the models' emphasis on extrinsic motivation (i.e. performance expectancy) with intrinsic motivation (Venkatesh et al., 2012). Hedonic motivation has been demonstrated to be a key predictor in a diversity of studies related to consumer technology acceptance and use (Brown & Venkatesh, 2005; Escobar-Rodriguez & Carvajal-Trujillo, 2014; Holbrook & Hirschman, 1982; Raman & Don, 2013; Van der Heijden, 2004; Venkatesh et al., 2012; Wang et al., 2014), which signifies its important addition to technology acceptance models. Therefore, it is assumed that this construct will play a significant role in predicting consumers' initial and continuous usage intention of a health-related smartphone app. In the context of this study, hedonic motivation entails everything that consumers perceive as fun, enjoying or entertaining while using a health app. For instance, integrated app features that encourage users to achieve their health goals; social features that support competing against other users via Social Network Sites like Facebook, or within the app community itself (Ahtinen et al., 2009); and data graphs that provide information about the user's progress in a creative manner (Ahtinen et al., 2009) can all be identified as hedonic values. Hence, the following hypothesis:

Hypothesis 5[a)]
Hedonic motivation positively affects initial and continuous usage intention of health-related smartphone apps.
[a)] non-users and user

2.3.6. Price Value

The price for using technological devices and services has been proven to affect consumers' usage adoption (Brown & Venkatesh, 2005; Chong, 2013; Coulter & Coulter, 2007; Dodds, Monroe & Grewal, 1991; Escobar-Rodriguez & Carvajal-Trujillo, 2014; Yu, 2012). The addition of price value - "consumers' cognitive tradeoff between the perceived benefits of the applications and the monetary cost for using them" (Venkatesh et al., 2012, p.161) as the second factor to the original UTAUT complements the research model with another construct related to resources (i.e. facilitating conditions) (Venkatesh et al., 2012). The authors stated that the price value is positive "when the benefits of using a technology are perceived to be greater than the monetary cost" (p.161). Within the context of this study, the benefits of using a health-related smartphone app - such as improved health, and the prevention of diseases, should be perceived as more important by consumers than the price they have to pay for using the app of interest.

Looking at it from a marketing perspective, price often has been defined together with the quality of the product or service in order to measure its perceived value (e.g. Zeithaml, 1988; Zhou, 2008). Although a general trend can be seen towards low-priced apps seeing that most apps are free of charge and paid apps increasingly offered just about the minimum rate of 0.89 euros (Mroz, 2013), it can be argued that for health-related smartphone apps, the price will play a significant role in influencing initial usage intention. Considering the infinite options of health-related smartphone apps and their differences in terms of quality (Mroz, 2013), the price could function as a validity pointer and help prospective users to assess their value. Moreover, when engaging in health-related behavior, users may want to be sure that the health services provided by the app provider are reliable and safe. A recent study about diabetes mobile applications found that compared to free apps, paid apps are more likely to provide qualified health services (Caburnay et al., 2015). Similarly, West et al. (2012) found that priced health apps are perceived as more reliable and trustworthy.
The hypothesis is as follows:

Hypothesis 6[b)]
Price Value positively affects initial usage intention of health-related smartphone apps.
[b)] non-users

2.3.7. Habit

The third construct that has been added to the original UTAUT by Venkatesh et al. (2012) is habit, as it has been proven to be an important predictor of technology usage behavior (e.g., Davis and Venkatesh 2004; Escobar-Rodriguez & Carvajal-Trujillo, 2014; Kim & Malhotra 2005; Kim, Malhotra & Narasimhan, 2005; Limayem, Hirt & Cheung, 2007). Habit is equated with a consumer's automatic use of an information technology that results from prior experiences (Kim et al., 2005; Venkatesh et al., 2012). There are two distinct theoretical viewpoints that explain the effect of habit on technology usage (De Guinea & Markus, 2009; Kim et al., 2005; Limayem et al., 2007; Venkatesh et al., 2012). On the one hand, the "habit/automaticity perspective" (HAP) justifies that use of technology is an automatic response to routinized behavior rather than a conscious processing (De

Guinea & Markus, 2009; Kim et al., 2005; Limayem et al., 2007; Venkatesh et al., 2012). On the other hand, the "instant activation perspective" (IAP) explains habit as the result of cognitive processing (Kim et al., 2005). This implies, with continuous technology usage, usage intentions are stored in the minds of consumers', and activated once the behavior takes place (Kim et al., 2005; Venkatesh et al., 2012). The difference between these two perspectives "is whether conscious cognitive processing for the makeup of intention is involved between the stimulus and the action" (Venkatesh et al., 2012, p.164). Consequently, it can be assumed that these two underlying theories of habit (i.e. HAP and IAP) also function together when investigating the role of habit on continuous usage intention.

Within the scope of this study, habit is seen as an acquired behavioral pattern that suggests the need to regularly use a health-related smartphone app. As this factor becomes redundant for initial usage intention, it will act as a distinguishing determinant between the two models of investigation. It is assumed that once a consumer is routinized in using his or her health app (e.g. using a fitness app each time during a running session), the automaticity of it will predict continuous usage intention. Furthermore, it is plausible that when consumers engage in health-related behavior (i.e. using a fitness app during a running session), initial usage intentions will be re-activated, so that continuous usage intention is positively affected. Hence, the following is hypothesized:

Hypothesis 7[c)]
Habit positively affects continuous usage intention of health-related smartphone apps.
[c)] users

2.4. Identifying Additional Factors Relevant for Health App Usage

The UTAUT 2 has been proposed to investigate technology acceptance and usage in the consumer context (Venkatesh et al., 2012). While it is a rather recent model, it has been studied in a diversity of fields. Its application in the health care context however, is still new and needs further understanding. Therefore, this study aims to contribute theoretical knowledge in the domain of consumer health technology by identifying additional factors relevant for health app usage. Carrying out this added variable approach (Holden & Karsh, 2010), the present study seeks to better understand the factors predicting initial and continuous usage intention of health-related smartphone apps. Three factors were added to both research models: Trust in the app provider; perceived privacy risks of using a health-related smartphone app; and consumers' valuation of their health.

2.4.1. Trust in the Health App Provider

Trust has been identified to affect consumer acceptance and use of technology within a diversity of studies (El-Wajeeh et al., 2014; Escobar-Rodriguez & Carvajal-Trujillo, 2014; Gefen, Karahanna & Straub, 2003; Min, Ji & Qu, 2008; Pavlou, 2003; Tung, Chang, Chou, 2008; Wu & Chen, 2005; Wu, Huang & Hsu, 2014; Zhou et al., 2010). In e-commerce for example, trust captures consumers' willingness to "become vulnerable to [the] Web retailer" (Pavlou, 2003, p.106), whereas in the healthcare context, trust is build upon the trustworthiness of the health app provider (Akter et al., 2011). In their study, Akter et al. (2011) argue that trustworthiness functions as a precursor of consumer trust, which then affects usage intention. Based on these findings, the study at hand follows the thoughts of Akter et al. (2011).

Considering the numerous adoption barriers of health-related smartphone apps, including the lack of regulation within the healthcare system, and the high amount of third-party apps that make it difficult for consumers to find a good quality health app (Akter, D'Ambra & Ray, 2011; Funk, 2013; Mroz, 2013), it can be argued that trusting the health app provider is crucial for user adoption (Akter et al., 2011; PwC, 2013). It is assumed that consumers, who trust the health app provider to provide reliable health services and to satisfy their health needs, are more likely to intend using a health-related smartphone app than consumers who doubt the app provider's commitment. Especially continuous usage intention will greatly depend on the confirmed trusting beliefs (Akter et al., 2011). It is hypothesized that:

Hypothesis 8[a)]
Trust in the app provider positively affects initial and continuous usage intention of health-related smartphone apps.
[a)] non-users and user

2.4.2. Perceived Privacy Risks of Using a Health App

Next to the importance of trusting the app provider, this study argues that consumers also estimate the perceived privacy risks of using a health-related smartphone app. In a study about technology acceptance models for mobile health systems, El-Wajeeh et al. (2014) found that data privacy is an important determinant for the acceptance of health-related mobile applications. However, using a health-related smartphone app is not so private. Timothy Zevnik (2012), expert in mobile healthcare, illustrates that not only are data being tracked related to health (e.g. height, weight, performances) but also general data related to the consumer such as age and gender. Together with the device's location and identification number these data are often forwarded to other companies including advertising agencies, third parties or other developers without "users' awareness or consent" (Zevnik, 2012). Therefore, perceived privacy risks of using a health-related smartphone app, is the outcome of lacking transparency between the app provider and the app user, as many smartphone apps don't inform users about what data is being gathered, much less what it is used for. As a result, consumers might associate the health benefits obtained from using a health-related smartphone app with privacy loss, resulting in greater perceived privacy risks (Pavlou, 2003; Sweeney, Soutar & Johnson, 1999).

Within the context of this study, perceived risks entail regulatory or safety errors a consumer could experience while using a health-related smartphone app; that is, risks related to patient safety and data privacy. According to PricewaterhouseCoopers[a] (2012), this is one of the most critical adoption barriers of mobile health services. Considering these findings, it can be argued that consumers who perceive greater risks with using a health-related smartphone app are less likely to intend using such service. Additionally, it can be assumed that the more trust consumers have in the health app provider, the fewer risks will be associated with using the health-related smartphone app. Therefore, the following hypotheses are formulated:

Hypothesis 9[a)]

Perceived privacy risks negatively affect initial and continuous usage intention of health-related smartphone apps.

[a)] non-users and user

Hypothesis 10[a)]

Trust in the app provider positively affects the privacy risks perceived from using a health-related smartphone app.

[a)] non-users and user

2.4.3. Consumers' Valuation of Health

Consumers' valuation of their own health is a crucial addition to the research model, as it is anticipated that a consumer's assessment of his or her own health is an important factor in predicting usage intention of health-related smartphone apps. Next to performance expectancy, this self-developed scale presents another construct based on theoretical notions from health behavior theories. Several researchers have used theoretical notions from the Protection Motivation Theory (PMT) and the Health Belief Model (HBM) to predict patient and consumer health behaviors (Janz & Becker, 1984; Milne et al., 2000; Milne et al., 2002; Rosenstock et al., 1988; Schwarzer, 2008; Smith & Stasson, 2000; Sun et al., 2013). Considering that a health-related smartphone app is a self-management tool (Or et al., 2010), it presents an intervention leading to health behavior change.

To operationalize this construct adequately, it is necessary to define health. The World Health Organization (WHO) defines health as "a state of complete physical, mental and social well-being" including "the absence of disease or infirmity" (WHO, 1948). Consequently, a healthy lifestyle implies the achievement and maintenance of one's mental, physical and emotional well being in order to prevent (chronic) diseases (Simons et al., 2013). It can be argued that a consumer who believes that it is important to follow a healthy lifestyle, with the presumption that it would improve the condition of his or her health, will be more likely to intend using a health-related smartphone app. Therefore, the following is hypothesized:

Hypothesis 11[a)]
Valuation of health positively affects initial and continuous usage intention of health-related smartphone apps.
[a)] non-users and user

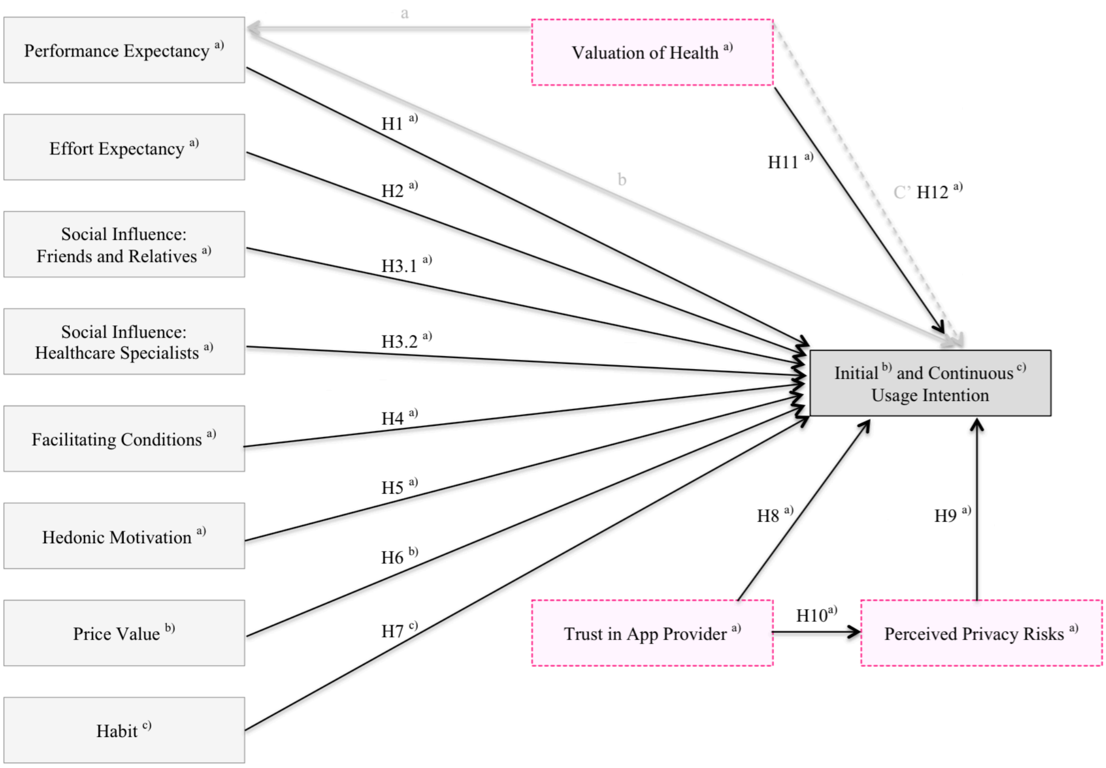
Furthermore, while investigating the determinants of health-related behavior, many researchers have focused on the benefits patients expect to gain when engaging in such behavior (i.e. health locus of control) (Norman, 1995). However, many have failed to consider the antecedents of expected health benefits. According to the Social Learning Theory (SLT), the intention to engage in health-related behavior is not only based on expected benefits, but also on the value attached to these benefits (i.e. health value) (Norman, 1995). Within the context of this study, it means that valuation of health is not only predicted to have a positive direct impact on usage intention of a health-related smartphone app, but also indirectly through performance expectancy. In other words, consumers' valuation of their health causes them to expect health benefits from using a health-related smartphone app, which ultimately, increases their intention to use such service. Hence, the final hypothesis is formulated:

Hypothesis 12[a)]
The effect of consumers' valuation of health on initial and continuous usage intention of health-related smartphone apps will be mediated by their performance expectancy.
[a)] non-users and user

Figure 3 depicts the research model proposed for investigating initial and continuous usage intention of health-related smartphone apps. The fundamental factors of the UTAUT 2 model (i.e. performance expectancy, effort expectancy, social influence, facilitating condition, hedonic motivation, price value, and habit) were modified to reflect the health app context; and further factors relevant for health app usage (i.e. trust in the app provider, perceived privacy risks of using a health-related app, and consumers' valuation of health) were added to complete the research model.

Figure 3

Proposed research model for initial and continuous usage intention of health-related smartphone apps



a) non-users and user, b) non-users, c) users

The relevance of the factors is marked by a), for both initial and continuous usage intention by b), for initial usage intention only, and by c) for continuous usage intention only. The arrows indicate the direction of the anticipated effect from the predictor variable to the outcome variable. Straight-lined arrows designate a direct effect, while dashed ones suggest an indirect effect. The mediated effect between valuation of health and usage intention is represented in light-grey color.

3. Methods

After presenting the theoretical support, the this chapter will elaborate on the methodology of investigating factors predicting initial and continuous usage intention of health-related smartphone apps among Dutch users.

3.1. Research Design

This study uses a correlational research design to explore the relationships between the predictor variables and the two outcome variables (i.e. (1) initial usage intention and (2) continuous usage intention) respectively. By means of a non-experimental, one-shot online questionnaire, this study aims to provide insights to what extend the value of the outcome variables are affected by the values of the predicting factors. Causal relationships, however, are not assessed, as these are impossible to prove from the measured associations (Dooley, 2001).

3.2. Procedure

Due to the high smartphone penetration in the Netherlands, the Dutch market offers prosperous ground for mobile health services such as health-related smartphone apps. In order to gain insights to health app-related behavior among Dutch users (De Veaux, Velleman & Bock, 2014), the study was conducted in the Netherlands.

A quantitative measurement instrument has been chosen for the collection of data, as the Internet as a medium is able to reach a vast amount of respondents (Funk, 2013). The online questionnaire was created with the survey tool builder qualtrics.com. Before it was administered, a Dutch native speaker translated the questionnaire, and verified the wording of items in order to reduce translational bias. Subsequently, the questionnaire was pre-tested by means of convenience sampling among Dutch university students (n = 9) to ensure questions are understood correctly and answered within the planned time frame. The pre-test facilitated in decreasing threats related to construct validity, which is a common concern for correlational research designs (Babbie, 2009).

The data collection process lasted from December 2014 to March 2015. Participants were recruited by means of several approaches. Firstly, the author's private contacts were addressed via e-mail, Facebook, and LinkedIn, with an encouragement to forward the online questionnaire (snowball sampling). Secondly, the author distributed the online questionnaire on Twitter as well as online fora and platforms related to health and innovative technologies. And lastly, participants were acquired from the online service 'Respondentendatabase.nl'.

3.3. Participants

Quantitative data were collected from a sample of N = 527 adults, of which 80 questionnaires were discarded because of missing responses. Participants were divided into two groups (non-users and users) based on whether, at this time point; they had a health-related app installed on their smartphone. This resulted in N = 179 non-users and N = 268 users. Because the installation of an app does not necessarily imply its usage, poor quality responses that could jeopardize results of the users participant group have been removed. These included responses with a '0' times usage per month of the health-related app or responses indicating no usage because the health app came with the participant's smartphone operating system (i.e. 'Health' from Apple's iOS or 'S Health' from Samsung's Android). Together with the removal of outliers, this process pulled in N = 373 responses useful for data analysis, consisting of N = 160 non-users and N = 213 users. This partition was created in order to specifically reflect the different attitudes with regards to initial and continuous usage intention of health-related smartphone apps between these two participant groups.

Table 1 depicts the demographic information of both participant groups.

Table 1
Demographic information of the participant groups

Demographic characteristics	Min	Max	M	SD
Age[b)]	19	82	40.11	16.17
Age[c)]	18	71	32.12	12.78
	Frequency[b)]	Percentage[b)]	Frequency[c)]	Percentage[c)]
Gender				
Male	89	55.6	99	46.5
Female	71	44.4	114	53.5
Education				
Middelbare School	22	13.8	18	8.5
MBO	35	21.9	33	15.5
Bachelor	63	39.4	97	45.5
Master	28	17.5	54	25.4
Doctorate	7	5	7	3.3
Other	5	3.1	4	1.9
Occupation				
Student	44	27.5	111	52.1
Employed	60	37.5	64	30.0
Self-employed	11	6.9	18	8.5
Unemployed	19	11.9	5	2.3
Retired	8	5.0	6	2.8
Other	18	11.3	9	4.2
Total	160	100	213	100

[b)] non-users, [c)] users

The non-users group includes adults aged between 19 and 82 years (M = 40.11, SD = 16.17), whereas the users group includes adults aged between 18 and 71 years (M = 32.12, SD = 12.78). Notably, health-related smartphone app users seem to be younger than non-users. Both groups demonstrate a nearly equal balance between males and females, although it is worth mentioning that males are slightly dominating the non-users group (n = 89 males > n = 71 females), whereas females are prevailing among the users group (n = 114 females > n = 99 males). Furthermore, there is little difference in terms of education between the non-users and users of health-related smartphone apps. The highest obtained education for both participant groups is a Bachelor's degree (non-users: n = 63, users: n = 97). A slight difference can be detected in terms of occupation: While the majority of non-users (37.5%) were employed at the time of inquiry (n = 60), about half of the users groups (52.1%) were students (n = 111).

Table 2 provides information about the participants' smartphone usage and general app experience.

Table 2
Information related to participants' smartphone app experiences

Characteristic		Frequency[b)]	Percentage[b)]	Frequency[c)]	Percentage[c)]
Smartphone Operating System					
	Android	110	68.8	102	47.9
	iOS	34	21.3	107	50.2
	Windows	12	7.5	3	1.4
	Other	4	2.5	1	0.5
App experience in years					
	< 1	31	19.4	9	4.2
	1 - 3	58	36.3	70	32.9
	3 - 5	47	29.4	84	39.4
	> 5	24	15.0	50	23.5
Number installed apps					
	< 5	40	25.0	7	3.3
	6 - 10	47	29.4	40	18.8
	11 - 20	37	23.1	67	31.5
	> 20	36	22.5	99	46.5
Total		160	100	213	100

[b)] non-users, [c)] users

The smartphone of most non-users (n = 110) works on the operating system 'Android', whereas Apple's 'iOS' slightly prevails among the users groups (n = 107). However, there is almost an equal balance between the 'Android' and 'iOS' smartphone operating systems among the users participant group ('Android' n = 102). This is in line with findings from market research, which also report a leading market share of Android's operating system among the Dutch app market (69%), compared to iOS (22%) (as of 2013, Oosterveer, 2013). In general, users of health-related smartphone apps are somewhat more experienced in general app usage than are non-users, and have more apps installed on their smartphone (i.e. more than 20 apps).

Furthermore, participants of the users group were asked about the number of health-related apps installed on their smartphone. Table 3 summarizes health-related smartphone app experiences among the users group.

Table 3
Information related to smartphone health app experiences of the users participant group

Characteristic	Min	Max	M	SD
Health app usage per month*	1	60	10.77	10.65

	Frequency	Percentage
Number installed health apps		
1 - 2	148	69.5
3 - 4	49	23.0
> 5	16	7.5
Most used health app		
RunKeeper	38	17.8
MyFitnessPal	15	7.0
Health (Apple's health app)	12	5.6
Nike Running	8	3.8
Runtastic	8	3.8
Sleep Cycle	8	3.8
Other	< 7	< 3
Total	213	100

* based on most used health app

Most users (n = 148) reported to have between one and two health-related apps installed on their smartphone. The fitness app RunKeeper appears to be the most used health app (17.8%). Users, who participated in this study, use their health-related smartphone app between 1 and 60 times per month. The average usage per month is about 10 times (M = 10.77, SD = 10.65).

3.4. Measurement Instrument

The online questionnaire was build upon four different sections. In the first part, participants were given a brief introduction with regards to the purpose and participation conditions of the study. An overview of the most popular health apps (based on an analysis of the most downloaded apps within the category 'Health and Fitness' of the Google Play and Apple's app store) served as an introductory purpose. The second part included demographic data according to age, gender, highest level of education, and current occupation of the participants. The third part asked about participants' experience with health-related smartphone apps and apps in general.

Based on the research objective and hypotheses, the final part of the questionnaire consisted of items measuring the hypothesized factors predicting initial and continuous usage intention of health-related smartphone apps. Suggested measurement items, derived from an extensive literature review (see chapter 2), helped define questions per variable to enhance validity and reliability. All items have been adjusted to fit the context of health app usage. 39 items were grouped into 10 constructs for each research model, and were measured on a 7-point Likert scale (1-strongly disagree/7-strongly agree), due to convenient direct digital transformation (Babbie, 2009). An overview of all scales used for the measurement instrument in can be found in Table 4.

Table 4

Scales used for the measurement instrument

Constructs	Items	Code
UTAUT2 factors		
Performance Expectancy (PE) [a] (Venkatesh, Thong & Xu, 2012)		
	Using [a/this] smartphone health app [would] increase[s] my chances of becoming healthier.	PE1
	Using [a/this] smartphone health app [would] help[s] me to prevent diseases.	PE2
	Using [a/this] smartphone health app [would] help[s] me to manage my health.	PE3
	[A/This] smartphone health app [would be/is] useful in my daily life.	PE4
Effort Expectancy (EE) [a] (Venkatesh, et al. 2012)		
	Learning how to use [a/this] smartphone health app [would be/is] easy for me.	EE1
	My interaction with [a/this] smartphone health app [would be/is] clear and understandable.	EE2
	I [would] find [a/this] smartphone health app easy to use.	EE3
	It [would be/is] easy for me to become skillful at using [a/this] smartphone health app.	EE4
Social Influence: Friends and relatives (SIfr) [a] (Venkatesh, et al. 2012)		
	Friends and relatives who are important to me think I should use [a/this] smartphone health app.	SIfr1
	I [would] use [a/this] smartphone health app because of the proportion of friends and relatives who use such an app.	SIfr2
	Friends' and relatives' suggestions [will] affect my decision to use [a/this] smartphone health app.	SIfr3
Social Influence: Healthcare specialists (SIsp) [a] (Venkatesh, et al. 2012)		
	Specialists (i.e. physicians, pharmacy, health insurance) think I should use [a/this] smartphone health app.	SIsp1
	I [would] use [a/this] smartphone health app because a specialists recommended it to me.	SIsp2
	Specialists' support and expertise [will] affect my decision to use [a/this] smartphone health app.	SIsp3
Facilitating Conditions (FC) [a] (Venkatesh, et al. 2012)		
	I [would] have the resources necessary to use [a/this] smartphone health app.	FC1
	I [would] have the knowledge necessary to use [a/this] smartphone health app.	FC2

	[A/This] smartphone health app is compatible with other technologies I use.	FC3*
	I can get help from others when I have difficulties using [a/this] smartphone health app.	FC4*
Hedonic Motivation (HM) a) (Venkatesh, et al. 2012)		
	Using [a/this] smartphone health app [would be/is] fun.	HM1
	Using [a/this] smartphone health app [would be/is] enjoyable.	HM2
	Using [a/this] smartphone health app [would be/is] very entertaining.	HM3
Price Value (PV) b) (Venkatesh et al., 2012; El-Wajee, Galal-Edeen & Mokhtar, 2014)		
	I would use a smartphone health app if it would be reasonably priced.	PV1
	A smartphone health app that is priced provides good value for the money.	PV2
	A smartphone health app that is priced will be helpful for obtaining good health services.	PV3
Habit (HAB) c) (Venkatesh, et al. 2012)		
	The use of this smartphone health app has become a habit for me.	HAB1
	I am addicted to using this smartphone health app.	HAB2
	I have to use this smartphone health app.	HAB3
	Using this smartphone health app has become natural to me.	HAB4
Initial Usage Intention (IUI) b) (Venkatesh, et al. 2012)		
	I intend to use a smartphone health app in the next 30 days.	IUI1
	I predict I would use a smartphone health app in the next 30 days.	IUI2
	I plan to use a smartphone health app in the next 30 days.	IUI3
Continuous Usage Intention (CUI) c) (Bhattacherjee, 2001)		
	I intend to continue using this smartphone health app rather than to discontinue its use.	CUI1
	I intend to continue using this smartphone health app rather than using any alternative service.	CUI2
	I will not discontinue my use of this smartphone health app.	CUI3
Additional factors relevant for health app usage		
Trust in the App Developer (TRU) a) (Akter, D'Ambra & Ray, 2011)		
	I [would] trust [a/this] smartphone health app developer to provide reliable health services and functions.	TRU1
	I [would] trust [a/this] smartphone health app developer's promises and commitment to satisfy my health needs.	TRU2
	I [would] trust [a/this] smartphone health app developer to meet my expectations.	TRU3
Perceived Privacy Risks (PR) a) (Escobar-Rodriguez & Carvajal-Trujillo, 2014)		
	I am concerned that [a/this] smartphone health app developer [would] collect[s] too much personal information from me.	PPR1
	I am concerned that [a/this] smartphone health app developer [would] use[s] my personal information for other purposes without my authorization.	PPR2
	I am concerned that [a/this] smartphone health app developer [would] share[s] my personal information with other entities without my authorization.	PPR3
	I am concerned that unauthorized persons (i.e. hackers) [would] have access to my personal information.	PPR4
	I am concerned that using [a/this] smartphone health app [would] cause[s] me to lose control over my information.	PPR5
Valuation of Health (VH) a) (self-developed scale; based on Norman, 1995)		
	The condition of my health would be better if I followed a healthy lifestyle.	VH1
	The condition of my health is important to me.	VH2*

Following a healthy lifestyle would have a positive impact on my future health.	VH3
It is important to me to follow a healthy lifestyle.	VH4

[a] non-users and users; [b] non-users; [c] users
[*] item was removed after reliability analysis

3.5. Reliability of Measurement Scales

As the study tests the robustness of the UTAUT 2 model within the mobile health context, all scales proposed by Venkatesh et al. (2012) (i.e. performance expectancy, effort expectancy, social influence, facilitating conditions, hedonic motivation, price value, and habit) have been adjusted for the purpose of this research. Social influence was particularly split into two sub-concepts (family and relatives; and healthcare specialists). The additional three scales were operationalized using different studies for theoretical foundation. Measuring the variables with multiple items ensures internal consistency, meaning that the measurement items will need to deliver consistent scores. To test whether the items used are reliable, the Cronbach's alpha was computed by means of the statistical software SPSS. An overview of the scores can be seen in table 5.

Table 5
Scale descriptives for all variables

Measurement Scales	Items[b]	α[b]	M[b]	SD[b]	Items[c]	α[c]	M[c]	SD[c]
Performance Expectancy	4	0.91	3.65	1.38	4	0.78	4.66	1.11
Effort Expectancy	4	0.90	5.21	1.07	4	0.92	6.04	0.74
Social Influence								
- Friends and relatives	3	0.79	2.28	1.12	3	0.84	2.64	1.46
- Healthcare specialists	3	0.73	3.52	1.33	3	0.89	2.00	1.29
Facilitating Conditions	2**	0.91	5.58	1.18	2**	0.78	5.97	0.79
Hedonic Motivation	3	0.92	3.84	1.37	3	0.82	5.21	1.02
Price Value	3	0.84	3.50	1.33				
Habit					4	0.83	3.60	1.35
Trust in App Provider	3	0.95	4.16	1.30	3	0.88	5.16	1.05
Perceived Privacy Risk	5	0.94	4.55	1.54	5	0.95	3.13	1.46
Valuation of Health	3*	0.78	5.51	1.05	3*	0.78	5.81	0.73
Usage Intention								
- Initial	3	0.97	2.35	1.39				
- Continuous					3	0.81	5.07	1.13

[b] non-users, [c] users
[*] 1 item deleted, [**] 2 items deleted
Note: constructs were measured on a 7-point likert scale (1 = totally disagree/7 = totally agree)

The constructs 'facilitating conditions' and 'valuation of health' indicated a non-sufficient alpha score in both models so that the weakest items were deleted for internal consistency. All other constructs used in this study have a Cronbach's alpha value above α 0.70, indicating sufficient internal consistency of the measurement scales (Cortina, 1993).

From the table can be derived that non-users as well as users of health-related smartphone apps generally agree in terms of effort expectancy (non-users: M = 5.21, users: M = 6.04), social influence from friends and relatives (non-users: M = 2.28, users: M = 2.64), facilitating conditions (non-users: M = 5.58, users: M = 5.97), and valuation of health (non-users: M = 5.51, users: M = 5.81). Furthermore, users of health-related smartphone apps feel more strongly about performance expectancy (M = 4.66), hedonic motivation (M = 5.21), and trust (M = 5.16); while non-users seem to be more concerned with the privacy risk associated by using a health-related smartphone app (M = 4.55), and perceive the expertise of healthcare specialists as more valuable than the users (M = 3.52). Generally, it can be said that users' intention to continue using their most used health-related smartphone app is higher than the initial usage intention of non-users. However, as in most cases, the standard deviation of the responses is well above one point away from the mean, participants did not always agree on the topics respectively.

The following section will present the result of the tested hypotheses and thereby, answer the research question about which factors predict initial and continuous usage intention of health-related smartphone apps.

4. Results

As the research objective is to find out which factors predict the initial and continuous usage intention of health-related smartphone apps, the first analysis included a correlation analysis for the non-users and users dataset respectively. Thereby, associations between the predictor and outcome variables will be detected. Although a predictive ability cannot be determined, a correlation analysis is useful to determine possible relationships (Dooley, 2001; Field, 2009).

4.1. The Relation Between the Predicted Factors and Usage Intention

As the dataset was split into non-users and users to predict initial and continuous usage intention of health-related smartphone apps respectively, two correlation analyses were conducted. The correlations matrix for the non-users model is presented in table 6. Often, the correlation of a variable with itself is 1, so that all diagonal correlations are the same (Dooley, 2001). As it is the case in this study, these correlations have been excluded.

Table 6

Correlations matrix of the non-users model

Construct	PE	EE	SIfr	SIsp	FC	HM	PV	TRU	PPR	VH	IUI
Performance Expectancy (PE)											
Effort Expectancy (EE)	.22**										
Social Influence (SIfr)	.54**	.10									
Social Influence (SIsp)	.54**	.26**	.52**								
Facilitating Conditions (FC)	.19*	.65**	.03	.29**							
Hedonic Motivation (HM)	.61**	.30**	.38**	.44**	.21**						
Price Value (PV)	.52**	.10	.40**	.43**	.04	.56**					
Trust in App Provider (TRU)	.42**	.09	.27**	.31**	.08	.50**	.41**				
Perceived Privacy Risks (PPR)	.09	-.00	.13	.12	-.11	.09	.03	.04			
Valuation of Health (VH)	.16*	.41**	.06	.27**	.46**	.30**	.12	.15	.20*		
Initial Usage Intention (IUI)	.53**	.13	.42**	.28**	.04	.54**	.41**	.46**	.10	.19*	

** Correlation significant at the .01 level (2-tailed)
* Correlation significant at the .05 level (2-tailed)

Of all the predictors, hedonic motivation (r = .54) and performance expectancy (r = .53) correlate best with the outcome variable (i.e. initial usage intention) so it is likely that these factors will be positive significant predictors for the initial usage intention of health-related smartphone apps. Further significantly positive, yet non-predictive factors on initial usage intention include trust in the app provider (r = .46), social influence from friends and relatives (r = .42), price value (r = .41), social influence from healthcare specialists (r = .28) (all significant at the .01 level), and valuation of health (r = .19) (significant at the .05 level). On a further note, facilitating conditions seem to be non-correlated with initial usage intention, as the correlation coefficient is the closest to zero (r = .04) (Dooley, 2001).

Table 7 presents the correlations matrix for the users model.

Table 7
Correlations matrix of the users model

Construct	PE	EE	SIfr	SIsp	FC	HM	HAB	TRU	PPR	VH	CUI
Performance Expectancy (PE)											
Effort Expectancy (EE)	.23**										
Social Influence (SIfr)	.30**	-.15*									
Social Influence (SIsp)	.20**	-.36**	.53**								
Facilitating Conditions (FC)	.19**	.61**	-.07	-.25**							
Hedonic Motivation (HM)	.17*	.30**	.17*	-.06	.26**						
Habit (HAB)	.52**	.16*	.26**	.24**	.06	.30**					
Trust in App Provider (TRU)	.27**	.26**	.16*	.08	.31**	.19**	.10				
Perceived Privacy Risks (PPR)	.11	-.29**	.22**	.25**	-.23**	-.03	.15*	-.15*			
Valuation of Health (VH)	.24**	.30**	-.02	-.11	.36**	.23**	.13	.23**	-.02		
Continuous Usage Intention (CUI)	.31**	.34**	.09	-.05	.31**	.35**	.49**	.24**	-.08	.25**	

** Correlation significant at the .01 level (2-tailed)
* Correlation significant at the .05 level (2-tailed)

Looking at the correlations matrix of the users model, it is self-evident that habit (r = .49) has the highest significantly positive correlation with continuous usage intention. Most likely, this factor will be a significant predictor to the outcome variable in further regression analysis. Additional significantly positive, yet non-predictive factors on continuous usage intention are hedonic motivation (r = .35), effort expectancy (r = .34), performance expectancy (r = .31), facilitating conditions (r = .31), valuation of health (r = .25), and trust in the app provider (r = .24) (all significant at the .01 level). Furthermore, the social influences from either friends and relatives or healthcare specialists, as well as perceived privacy risks, seem to be non-associated with continuous usage intention, as the correlation coefficient is the lowest among all predictor variables.

4.1.1. Testing for Multicollinearity

Correlations matrices additionally provide a first inspection on multicollinearity (Field, 2009), a condition where two or more of the predictor variables are highly correlated with each other (Disatnik & Sivan, 2014). Significant multicollinearity can endanger further statistical analyses like multiple regressions, as it is difficult to obtain a distinct estimate of the regression coefficients of a particular predictor variable on the outcome variable (Field, 2009; York, 2012). On a first glance at the correlations matrices, no multicollinearity can be detected, as there are no substantial correlations between all the predictor variables (i.e. r > .9) in either of the research models (Field, 2009). Nevertheless, some associations are quite high (r = .5 - .7). Therefore, collineary statistics were performed to test whether multicollinearity will be an issue in the regression analyses (York, 2012).

For both models, the tolerance statistics and the variance inflation factor (VIF) were calculated; a widely used measure to indicate the degree of multicollinearity (O'Brien, 2007). As the tolerance statistics show no values below 0.1, and the VIF's are no greater than 10, it can be safely concluded that there is no collinearity within either datasets and that regression models are not threatened (Field, 2009; O'Brien, 2007) (see Table 15, Appendix, p.52).

4.2. Hierarchical Regression on Usage Intention for the Predicted Factors

A hierarchical regression analysis was conducted for both research models in order to assess the effects of the different predictor variables on the outcome variables (Dooley, 2001; York, 2012). As the aim of this study is to investigate which factors determine initial and continuous usage intention of health-related smartphone apps respectively, the UTAUT 2 model has been complemented with factors relevant to health app usage. These include trust in the app provider, perceived privacy risks, and consumers' valuation of health. To determine the robustness of the proposed research models, hierarchical regression analyses were conducted to test the hypotheses formulated in chapter two. Furthermore, the results will determine whether the UTAUT 2 provides appropriate theoretical foundations for explaining technology acceptance and use in the context of consumer health technology, as known predictors from the UTAUT 2 were entered into the regression models first (Field, 2009). Table 8 presents the hierarchical regression analysis for the non-users model.

Factors from the UTAUT 2 were considered primary predictors for initial and continuous usage intention of health-related smartphone apps. Therefore, performance expectancy, effort expectancy, social influence, facilitating conditions, hedonic motivation, price value or habit, were inserted in the first block (model 1) of the regression equation, representing the first step in the hierarchy (Field, 2009). These predictors altogether account for a variability of 37% in initial usage intention of health-related smartphone apps (R^2 = .37). When the other three predictors trust in the app provider, perceived privacy risk, and valuation of health were added to the regression model (model 2), this value increased to 40% of the variance in initial usage intention (R^2= .40), accounting for an additional 4% (ΔR^2 = .04). Hence, the predictors hypothesized to be further relevant for health app usage improve the overall fit of the model just slightly (Dooley, 2001; Field, 2009).

Table 8

Hierarchical regression on initial usage intention for the proposed factors

	Regression Coefficients					
Models	B	SE B	β	R^2	Adj. R^2	ΔR^2
UTAUT2				**.40**	**.37**	
Constant	.06	.52				
Performance Expectancy	.26	.09	.26**			
Effort Expectancy	.03	.11	.02			
Social Influence: Friends and relatives	.24	.10	.20*			
Social Influence: Healthcare specialists	-.13	.09	-.13			
Facilitating Conditions	-.08	.10	-.07			
Hedonic Motivation	.35	.09	.34***			
Price Value	.07	.09	.06			
Proposed model				**.44**	**.40**	**.04**
Constant	-.84	.63				
Performance Expectancy	.24	.09	.24**			
Effort Expectancy	.03	.11	.02			
Social Influence: Friends and relatives	.25	.10	.20*			
Social Influence: Healthcare specialists	-.16	.09	-.15			
Facilitating Conditions	-.13	.11	-.11			
Hedonic Motivation	.25	.09	.24**			
Price Value	.04	.08	.03			
Trust in App Provider	.22	.08	.21**			
Perceived Privacy Risk	-.00	.06	-.00			
Valuation of Health	.16	.10	.12			

*** $p < .001$, ** $p < .01$, * $p < .05$

Among the significant positive predictors is performance expectancy ($\beta = .24$, $p < .01$), hedonic motivation ($\beta = .24$, $p < .01$), trust in the app provider ($\beta = .21$, $p < .01$), as well as social influence from friends and relatives ($\beta = .20$, $p < .05$). Therefore, hypotheses H1[b)], H3.1[b)], H5[b)] as well as H8[b)] are supported. Surprisingly, social influence from healthcare specialists has a negative coefficient ($\beta = -.15$), implying a reverse, yet non-significant ($p = .071$) effect on initial usage intention (Dooley, 2001; Field, 2009). Consequently, hypotheses H3.2[b)] could not be supported. Furthermore, it is worth noting that the effect from valuation of health on initial usage intention is moving toward the predicted direction ($p = .113$). Although marginally significant, hypothesis 11[b)] was not supported. The factors effort expectancy, facilitating conditions, price value, as well as perceived privacy risks showed no predictive power for the initial usage intention of health-related smartphone apps. Therefore, hypothesis H2[b)], H4[b)], H6[b)], and H9[b)] were not supported.

Table 9 presents the hierarchical regression analysis for the users model. Compared to the non-users models, the results demonstrate that the predicted UTAUT 2 factors independently (model 1: $R^2 = .33$) as well as with the added predictors (model 2: $R^2 = .34$), show a slightly smaller variance in usage intention. Consequently, trust in the app developer, perceived privacy risks, and valuation of health solely account for an additional 2% of the variance in continuous usage intention ($\Delta R^2 = .017$).

Table 9
Hierarchical regression on continuous usage intention for the proposed factors

Models	B	SE B	β	R^2	Adj. R^2	ΔR^2
	Regression Coefficients					
UTAUT2				**.35**	**.33**	
Constant	.65	.67				
Performance Expectancy	.03	.07	.03			
Effort Expectancy	.16	.12	.11			
Social Influence: Friends and relatives	.02	.05	.03			
Social Influence: Healthcare specialists	-.08	.06	-.09			
Facilitating Conditions	.23	.10	.16*			
Hedonic Motivation	.14	.07	.13*			
Habit	.36	.06	.42***			
Proposed model				**.37**	**.34**	**.02**
Constant	.45	.77				
Performance Expectancy	.00	.07	.00			
Effort Expectancy	.11	.12	.07			
Social Influence: Friends and relatives	.02	.06	.03			
Social Influence: Healthcare specialists	-.08	.06	-.10			
Facilitating Conditions	.17	.11	.12			
Hedonic Motivation	.12	.07	.11			
Habit	.37	.06	.44***			
Trust in App Provider	.11	.07	.10			
Perceived Privacy Risk	-.05	.05	-.06			
Valuation of Health	.11	.10	.07			

*** $p < .001$, ** $p < .01$, * $p < .05$

The only significantly positive predictor on continuous usage intention of health-related smartphone apps is habit (β = .44, p < .001), supporting hypotheses H7[c)]. However, it is worth noting that, although not significant, quite a few predictors are moving towards the predicted direction. Hedonic motivation (p = .085); trust in the app provider (p = .109); and facilitating conditions (p = .110) all proven to be marginally significant in explaining continuous usage intention. Nevertheless the corresponding hypotheses H5[c)], H7[c)], and H4[c)] were not supported. Similar to the non-users model, social influence from healthcare specialists has a negative, non-significant (p = .194) effect on continuous usage intention. Thus, hypothesis 3.2[c)] was not supported. Concluding, the other factors performance expectancy, effort expectancy, social influence from friends and relatives, perceived privacy risks, and valuation of health showed no predictive power on continuous usage intention of users' most used health-related smartphone app, meaning that hypotheses H1[c)], H2[c)], H3.1[c)], H8[c)], and H11[c)] were also not supported.

Overall, the proposed research models for initial and continuous usage intention of health-related smartphone apps show evidence for successful regressions, as each model predicts usage intention by more than 30% (De Veaux et al., 2014).

4.3. The Mediated Effect of Valuation of Health on Usage Intention

Next to the hypothesized direct effects, it was argued that in each model the effect from valuation of health on usage intention is mediated by performance expectancy. In other words, valuation of health acts as an antecedent to performance expectancy, implying the more consumers value their health, the more their would believe that using a health-related smartphone app provides them with health benefits, which ultimately, leads to increased usage intention. Table 10 presents the regression analyses to detect the mediating relationship between valuation of health and initial usage intention.

Table 10

Four step regression testing mediation of performance expectancy between valuation of health and initial usage intention

	Regression Coefficients				
Models	B	SE B	β	R^2	Adj. R^2
1				**.04**	**.03**
Constant	.94	.58			
Valuation of Health	.26	.10	$.19^{*}$		
Dependent Variable: Initial Usage Intention					
2				**.03**	**.02**
Constant	2.51	.58			
Valuation of Health	.21	.10	$.16^{*}$		
Dependent Variable: Performance Expectancy					
3				**.28**	**.27**
Constant	.41	.27			
Performance Expectancy	.53	.07	$.53^{***}$		
Dependent Variable: Initial Usage Intention					
4				**.03**	**.03**
Constant	-.35	.53			
Valuation of Health	.15	.09	.11		
Performance Expectancy	.51	.07	$.51^{***}$		
Dependent Variable: Initial Usage Intention					

*** $p < .001$, ** $p < .01$, * $p < .05$

According to Baron and Kenny (1986), three conditions have to be met for detecting mediation. Those include a significant effect for each of the simple regression equations (model 1–3). Then, model 4 should reveal that when the mediator variable is included to the regression equation, the effect between predictor and outcome variable is significantly decreased (Baron & Kenny, 1986). As can be derived from table 10, model 4 shows a full mediation, because initial usage intention is no longer affected by valuation of health, while performance expectancy remains significant. Therefore, it can be confirmed that the effect from valuation of health on initial usage intention is mediated by performance expectancy, supporting hypothesis H12[b)].

Table 11
Four step regression testing mediation of performance expectancy between valuation of health and continuous usage intention

	Regression Coefficients				
Models	B	SE B	β	R^2	Adj. R^2
1				**.06**	**.06**
Constant	2.79	.61			
Valuation of Health	.39	.10	$.25^{***}$		
Dependent Variable: Continuous Usage Intention					
2				**.06**	**.05**
Constant	2.58	.60			
Valuation of Health	.36	.10	$.24^{**}$		
Dependent Variable: Performance Expectancy					
3				**.10**	**.09**
Constant	3.58	.32			
Performance Expectancy	.32	.07	$.31^{***}$		
Dependent Variable: Continuous Usage Intention					
4				**.13**	**.12**
Constant	2.08	.61			
Valuation of Health	.29	.10	$.19^{**}$		
Performance Expectancy	.27	.07	$.27^{***}$		
Dependent Variable: Continuous Usage Intention					

*** $p < .001$, ** $p < .01$, * $p < .05$

Table 11 represents the mediator analysis for the users model. Clearly, the first three conditions for mediation are fulfilled, seeing that model 1-3 show significant effects (Baron & Kenny, 1986). However, model 4 reveals that valuation of health indeed has decreased in its effect on continuous usage intention when performance expectancy is controlled. Yet, the effect is still significant in determining continuous usage intention, implying a partial mediation. Nonetheless, hypothesis H12[c)] is supported.

4.4. The Effect of Trust in the App Provider on Perceived Privacy Risks

Finally, simple linear regression analyses for each model were conducted to test the effect from trust in the app provider on perceived privacy risks (Field, 2009). It was hypothesized that increased trust in the app provider would lower consumers privacy risks associated with using a health-related smartphone app.

Table 12 presents the simple regression analysis for the non-users model. Contrary to expectations, trust in the app provider shows no significant effect on perceived privacy risks of using a health-related smartphone app ($\beta = .04$, $p > .05$). Therefore, hypothesis H10[b)] could not be supported.

Table 12

Simple linear regression on perceived privacy risks for trust in the app provider of the non-users model

	Regression Coefficients				
Model	B	SE B	β	R^2	Adj. R^2
1				**.00**	**-.00**
Constant	4.33	.41			
Trust in App Provider	.05	.09	.04		

*** $p < .001$, ** $p < .01$, * $p < .05$

Table 13 presents the simple regression analysis for the users model. As expected, trust in the app provider has a significantly positive effect on perceived privacy risks ($\beta = -.15$, $p < .05$). This means that consumers who are more trusting in the app provider of their most used health app, perceive fewer risks in using the health app. Therefore, hypothesis H10[c)] is supported.

Table 13

Simple linear regression on perceived privacy risks for trust in the app provider of the users model

	Regression Coefficients				
Model	B	SE B	β	R^2	Adj. R^2
1				**.02**	**.02**
Constant	4.19	.50			
Trust in App Provider	-.21	.10	$-.15^{*}$		

*** $p < .001$, ** $p < .01$, * $p < .05$

The following table presents an overview of all tested hypotheses with the matching results for each research model. Out of the 10 hypothesized factors predicting initial and continuous usage intention of health-related smartphone apps, 4 were found significant in predicting initial usage intention, whereas continuous usage intention was found to be dependent by only one predictor.

Table 14

Overview of tested hypotheses

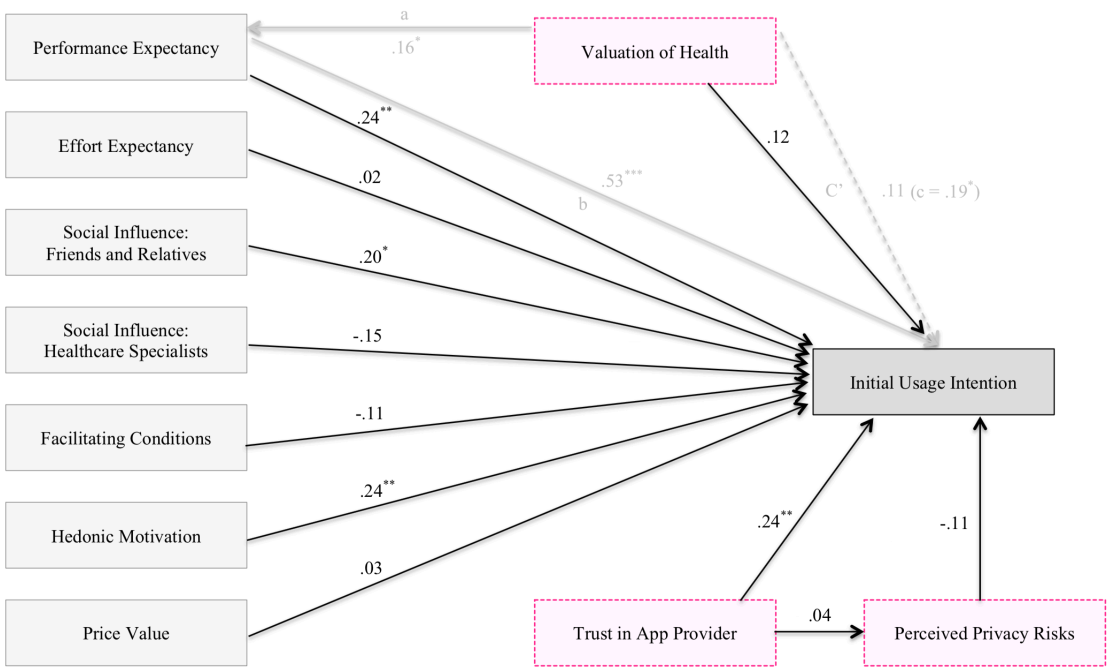
#	Hypotheses	Results
H1[a)]	Performance expectancy positively affects initial and continuous usage intention of health-related smartphone apps.	**Supported**[b)]
H2[a)]	Effort expectancy positively affects initial and continuous usage intention of health-related smartphone apps.	Not Supported[a)]
H3.1[a)]	Social influence from friends and relatives positively affects initial and continuous usage intention of health-related smartphone apps.	**Supported**[b)]
H3.2[a)]	Social influence from healthcare specialists positively affects initial and continuous usage intention of health-related smartphone apps.	Not Supported[a)]
H4[a)]	Facilitating conditions positively affect initial and continuous usage intention of health-related smartphone apps.	Not Supported[a)]
H5[a)]	Hedonic motivation positively affects initial and continuous usage intention of health-related smartphone apps.	**Supported**[b)]
H6[a)]	Price value positively affects initial usage intention of health-related smartphone apps.	Not Supported[a)]
H7[a)]	Habit positively affects continuous usage intention of health-related smartphone apps.	**Supported**[c)]
H8[a)]	Trust in the app provider positively affects initial and continuous usage intention of health-related smartphone apps.	**Supported**[b)]
H9[a)]	Perceived privacy risks negatively affect initial and continuous usage intention of health-related smartphone apps.	Not Supported[a)]
H10[a)]	Trust in the app provider positively affects the perceived privacy risks from using a health-related smartphone app.	**Supported**[c)]
H11[a)]	Valuation of health positively affects initial and continuous usage intention of health-related smartphone apps.	Not Supported[a)]
H12[a)]	The effect of consumers' valuation of health on initial and continuous usage intention of health-related smartphone apps will be mediated by their performance expectancy.	**Supported**[a)]

[a)] non-users and user, [b)] non-users, [c)] users

To clarify the theoretical models proposed for initial and continuous usage intention of health-related smartphone apps, the standardized regression coefficients (i.e. path coefficients) were placed on the matching arrows. Each value illustrates the strengths of the effect from the predictor to the outcome variable (Dooley, 2001). Figure 4 and 5 presents the research results for the factors predicting initial and continuous usage intention of health-related smartphone apps, respectively.

Figure 4

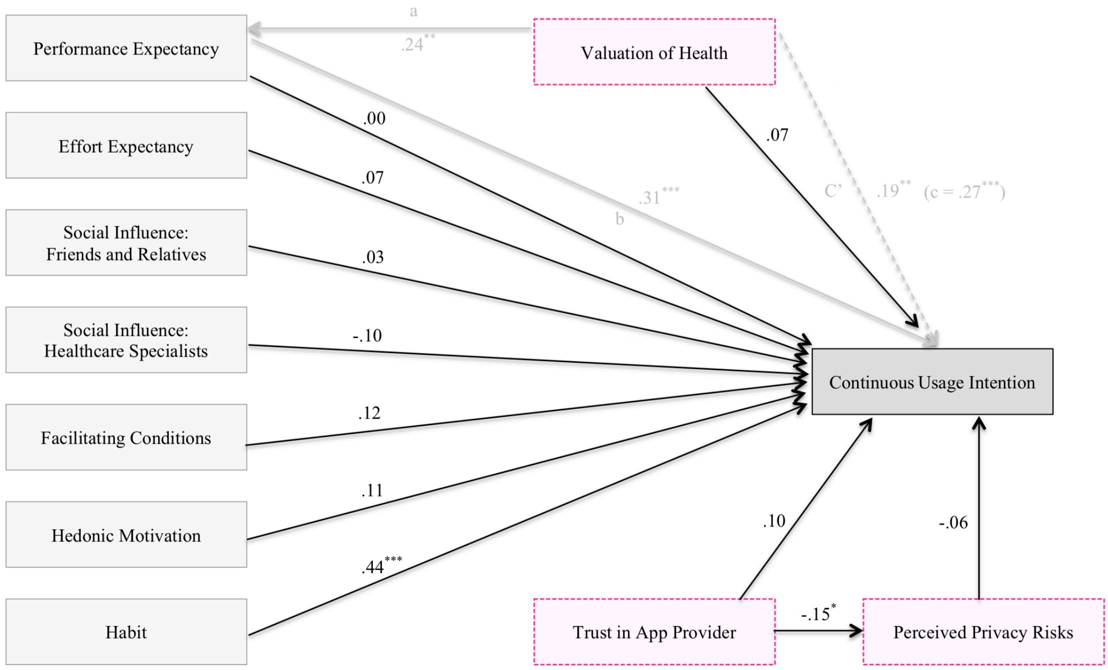
Research results for the factors predicting initial usage intention of health-related smartphone apps



*** p < .001, ** p < .01, * p < .05

Figure 5

Research results for the factors predicting continuous usage intention of health-related smartphone apps



*** $p < .001$, ** $p < .01$, * $p < .05$

In the final part of this study, the answer about the factors predicting initial and continuous usage intention of health-related smartphone apps will be discussed, so that conclusions can be drawn on how to successfully market these services among Dutch users.

5. Discussion and Conclusion

The present study investigated which factors determine initial and continuous usage intention of health-related smartphone apps. Factors of the UTAUT 2 such as performance expectancy, effort expectancy, social influence, facilitating conditions, hedonic motivation, price value, and habit) were used as a theoretical foundation and completed with additional factors (i.e. trust in the app provider, perceived privacy risks, and valuation of health) relevant for health app usage. The aim was to contribute to theoretical knowledge in the domain of consumer health technology, and further, to provide practical insights to app providers and healthcare practitioners on how to successfully market their services among Dutch users.

This final chapter will start by discussing the research results with regards to initial usage intention, followed by findings related to continuous usage intention. Afterwards, a comparison between these two research models will elaborate on the similarities and differences between initial and continuous usage intention of health-related smartphone apps. Then, the study's theoretical and practical relevance will be discussed. Ultimately, limitations will be addressed and directions for future research will be proposed.

5.1. Initial Usage Intention of Health-related Smartphone Apps

Results of the hierarchical regression analysis reveal that out of the ten hypothesized factors predicting consumers' initial usage intention, performance expectancy, hedonic motivation, and trust in the app provider were found to be equally strong predictors; closely followed by the social influence exerted by friends and relatives.

Firstly, the significance of performance expectancy confirms that the utilitarian value of health-related smartphone app usage strongly influences consumers' intention on whether or not to use such an application. This means, the more consumers believe that using a health-related smartphone app provides them with benefits such as improved health and the prevention of diseases, the more they are inclined to intend using this mobile health service. In line with many other technology acceptance studies in the consumer health context (e.g. El-Wajeeh et al., 2014; Or et al., 2010; Sun et al., 2013; Wang et al., 2014), this study shows that perceived usefulness and outcome expectations form the strongest predictor for usage intention. Moreover, results supported that consumers' valuation of health indirectly affects initial usage intention through the performance expectancy of health-related smartphone apps. Apparently, valuation of health by itself is not enough in predicting initial usage intention. Instead, the intention to engage in health-related behavior is based on the expected benefits, and the value consumers attach to these benefits (Norman, 1995).

Secondly, hedonic motivation was found to be a strong positive predictor of consumers' initial usage intention, which reflects findings of similar studies (e.g. Brown & Venkatesh, 2005; Escobar-Rodriguez & Carvajal-Trujillo, 2014; Raman & Don, 2013; Venkatesh et al., 2012; Wang et al., 2014). Seeing that hedonic motivation is of equal importance as performance expectancy, this study emphasizes the thought of Holbrook and Hirschman (1982) who proposed that consumers' perception of a product are not only affected by its utilitarian, but increasingly by hedonic values. That is, in addition to healthcare benefits, consumers need a health-related smartphone app to be fun, entertaining, and most of all, interesting. In his study, Funk (2013) discovered that during the usage of mobile health apps consumers are very fond of integrated reminders that support healthy lifestyle choices, and overall, appreciate tracking functions. Similarly, Ahtinen et al. (2009) report that consumers perceive data graphs as very entertaining. After all, the importance of hedonic values cannot be underestimated, as these are presumed key drivers in keeping users engaged in health-related behavior (Mroz, 2013).

Thirdly, social influence performed by friends and relatives has been confirmed to be a positive predictor of consumers' initial usage intention, which reflects results of similar studies (e.g. El-Wajeeh et al., 2014; Cheng et al., 2014; Muzaffar et al., 2014). For instance, Cheng et al. (2014) found that friends and parents influence physical activity in adolescents by providing social support. Likewise, subjective norm was the strongest predictor for healthy eating and physical activity intentions in a study conducted by Muzaffar et al. (2014). Results from the correlation analysis further reveal that there is a strong link between social influence of friends and relatives and the other significant predictors of initial usage intention (i.e. performance expectancy, hedonic motivation, trust in the app provider). This suggests that the influence of friends and relatives is key in the attitude formation about the advantages of using a health-related smartphone app (Or et al., 2010).

Lastly, as one of the added factors to the UTAUT 2, trust in the app provider was found to be another significant predictor for initial usage intention. This is in line with several studies in the context of consumer acceptance of technology (e.g. Akter et al., 2011; El-Wajeeh et al., 2014; Min et al., 2008). The effect can be explained by one of the many identified adoption barriers of mobile health services: The myriad of options and information surrounding health-related smartphone apps, which make it difficult for consumers to know which health apps are of good quality. After all, consumers simply want to trust the app provider to satisfy their health needs by providing reliable health services (Geiselhart, 2015). The importance of trusting the app provider who works in line with healthcare systems cannot be underestimated, as it is a crucial factor for the widespread adoption of health-related smartphone apps and mobile health services in general (PwC, 2013).

Next to the above-mentioned significant predictors, the insignificance of one of the predictors distinguishing between initial and continuous usage intention of health-related smartphone apps has be acknowledged. Price value was reported as non-significant in predicting initial usage intention, which can be reasoned in the following way: On the one hand, even when priced, health-related smartphone apps are not expensive. Consequently, its effect on consumers' initial usage intention is very low compared to the other predictors in the model. On the other hand, smartphone users have become quite price sensitive (Mroz, 2013), so that a priced health app is perceived more as an obstacle. Nevertheless, results of the correlation analysis show that price value correlates quite strongly with performance expectancy and hedonic motivation. Regardless of its insignificance on initial usage intention, to some extend this correlation confirms that the price of health app acts as a validity pointer of quality (Zeithaml, 1998; Zhou, 2008).

5.2. Continuous Usage Intention of Health-related Smartphone Apps

With regards to continuous usage intention, habit was found to be the strongest and only predictor, which is in accordance with several studies in the context of technology use (e.g. De Guinea & Markus, 2009; Escobar-Rodriguez & Carvajal-Trujillo, 2014; Kim et al. 2005; Limayem et al. 2007; Venkatesh et al., 2012). In this study, habit was defined as an acquired behavioral pattern that suggests the need of regularly using a health-related smartphone app. This study confirms that continuous usage intention is determined by a combination of conscious and unconscious reasoning (De Guinea & Markus, 2009; Venkatesh et al., 2012). That is to say, a user's intention to continue using his health app is determined by the automaticity of usage, which implies unconscious processing. At the same time, when using a health-related smartphone app a user will automatically recall initial usage intentions (e.g. to manage health, or prevent diseases), implying that continuous usage intentions are determined by the conscious goal of achieving health benefits. Results of the correlation analysis revealed that habit strongly correlates with performance expectancy, giving support for this conclusion. Research conducted by De Guinea and Markus (2009) also justify that "habits are developed as behaviors that appear to be satisfactory in fulfilling some goal" (p.439). This means when using the health-related smartphone app, the goal of achieving health benefits is assumed to be intentional while the actual usage of the smartphone app is understood as an unintentional process (De Guinea & Markus, 2009, p.440).

However, considering that habit was found to be the only predictor for continuous usage intention, it can be concluded that the unconscious processing outperforms cognitive reasoning. Therefore, it is not surprising that the other predictor related to health benefits such as performance expectancy is not significant in predicting continuous usage intention. Other studies related to consumer technology usage reported similar findings (e.g. Kim et al., 2005; Venkatesh et al., 2003). In their study, Venkatesh et al. (2003) described that with increased usage experience, users' evaluations on usage intention decreased.

Furthermore, it was confirmed that trust in the app provider positively affects the perceived privacy risks of using a health-related smartphone app. This means that health app users are less concerned about the maltreatment of their personal data when they trust the app provider to act in their best interest. Looking at the descriptive statistics, users are quite experienced in terms of general app usage and also, have many apps installed on their smartphone. This could imply that with continued usage, positive experiences such as fulfilled expectancies lead to fewer negative expectations like the loss of privacy.

5.3. Comparing Non-users' and Users' Health App Usage Intention

Although users and non-users seem to value different aspects when intending to use a health-related smartphone app, there are also some similarities that should be emphasized. In the first place, it is important to notice the insignificance of perceived privacy risks on usage intention. This is counterintuitive, bearing in mind that millions of health data are being collected during app usage (research2guidance, 2014). Theoretically, app providers analyze the data with tracking systems such as Google Analytics or App Annie in order to offer more personalized services to the user (Mroz, 2013). In practice however, many transfer the users' personal data to third parties, or other service providers (Zevnik, 2012). As perceived privacy risks have been identified as a real issue for the adoption of mobile health services (El-Wajeeh et al., 2014; PwC, 2013), this result is very surprising. Nevertheless, two reasons could explain this outcome. Firstly, users might take their overall app experiences as reference points for judging privacy risks (El-Wajeeh et al., 2014). Thus, if a user never encountered malicious experiences in terms of data privacy, they cannot identify with any concerns about the privacy risks usually associated with health app usage. Besides, users might not even be aware of what happens with their personal data without their consent. Secondly, users might not perceive any privacy risks because this study specifically investigated attitudes about health-related smartphone apps directed at consumers. It can be assumed that in a medical context where patients enter more sensitive health data (e.g. for diabetes management), perceived privacy risks would be significantly important in determining initial and continuous usage intention. This can be supported by the results of a study conducted by El-Wajeeh et al. (2014), who found that data privacy has an insignificant effect on usage intention when tested among general users; but becomes significant among actual patients.

Another surprisingly insignificant effect has been found on initial and continuous usage intention of health-related smartphone apps for the influence of healthcare specialists. This shows that social influence from known people such as close friends and family members outperforms the expertise of specialists. Suitably, McPhilliamy (2015) states: "The influence that a loved one can have on a relative's health decision is enormous and can outweigh that of even a primary care physician.”. Furthermore, social influence exerted by healthcare specialists shows a reverse direction on both initial and continuous usage intention, suggesting that when a medical practitioner recommends the usage of a health-related smartphone app, consumers would be less likely to intend using such an application. While this might not seem logical, it is possible that since recommendations for health app usage form a specialists do not reflect reality yet, participants might have found it difficult to identify with this scenario and thus, don’t believe that it would influence their initial (or continuous) usage intention.

As a final observation, effort expectancy as well as facilitating conditions for both initial and continuous usage intention were found to be insignificant. The insignificance of effort expectancy can be explained by the fact that apps and smartphones in general have become a very integrated into consumers every day life (Funk, 2013; Mroz, 2013). As a consequence, the usage of a health-related smartphone app is not perceived as difficult. Also, effort expectancy might be an irrelevant predictor in this study due to the dominating number of young and middle-aged people who participated in this study, as those are known to have a higher technical affinity (Mroz, 2013). Surely, this effect would gain significance when tested solely among the elderly. With regards to facilitating conditions, the insignificance of this factor can be explained by the lack of compatibility of current health-related smartphone apps with other technological devices, or even by the limited amount of those itself. Seeing that wearables are not yet fully integrated into mobile health systems and in early developments, consumers may don’t really have the resources for effectively using a health-related smartphone app, and thus, facilitating conditions are not a determinant for usage intention.

In sum, very different aspects determine consumers’ initial and continuous usage intentions. Performance expectancy, hedonic motivation, trust in the app provider, and social influence of friends and relatives are important factors in the intention formation of initial health app usage. However, as usage becomes routinized it is the automaticity of health app usage itself that determines continuous usage, which explains why habit is the only significant factor for predicting continuous usage intention.

5.4. Theoretical Relevance

The theoretical relevance of this study is threefold. Firstly, most previous studies in the health domain have conducted their research with rather general technology acceptance models (e.g. TAM). However, as health technology acceptance is very specific, it requires a deliberate variation. By taking the extended unified theory of technology acceptance and use (UTAUT 2) and refining it with health behavior theories (i.e. HBM; PMT; SLT), this study adds further knowledge to technology acceptance and use in the domain of consumer health technology. Holden and Karsh

(2010) confirm, "theory based additions to the prediction and explanation of health IT use and acceptance is a welcomed approach" (p.167). Secondly, other studies researching technology acceptance in the health domain have particularly focused to the professional context (e.g. Kijsanayotin et al., 2009). So far, little was kwon about the consumer's perspective. Understanding their behavior with regards to health-related smartphone apps is crucial considering the increasing importance of mobile health solutions in the future. Thirdly, this study clearly distinguishes between initial and continuous usage intention. Past studies primarily investigated consumer adoption of health technologies (e.g. Sun et al., 2013), but continuous usage intention has not been explored (Chen, Meservy & Gillenson, 2012). Therefore, the study contributes by filling this gap. Future research about health technologies should embrace these findings and recognize that (1) research in the health domain ask for contextualization of established technology acceptance models; (2) for a clear distinction between the context of consumer and professional healthcare; and (3) acknowledge that there is a difference between initial and continuous usage intention - accordingly, distinct factors will be needed for investigation.

5.5. Practical Implications

The aim of this study was further to advice health app providers and healthcare practitioners how health-related smartphone apps could be successfully targeted to achieve widespread user adoption. Based on the research results presented in chapter four, this study provides health app providers ideas for marketing their services to the Dutch consumers.

To overcome adoption barriers, health app providers need to stand out in terms of quality and clearly communicate the app's added value to prospective users. Healthcare benefits, reliable services and information, as well as captivating and personalized app usage are all values that should be anchored in the unique selling proposition and determine marketing activities. For instance, app providers should comply with the latest rules and regulations of medical, health, and patient safety standards. Also, app updates are an extremely important determinant for the development of the app in terms of new functions and bug fixes (Mroz, 2013). By means of press releases and the corporate website or blog, health app providers could communicate their latest efforts in providing safe and reliable health services to the app user. This user-centered approach will most likely induce greater trust in the app provider, as consumers are going to recognize the app provider's commitment to satisfy their health needs.

Next to these utilitarian, health app providers should communicate hedonic values of their app. As this study showed, prospective users place great importance on the hedonic gratifications from using a health-related smartphone app. Dependent on the type of health app, measures to integrate hedonistic features are abundant: These could range from possibilities to celebrate achieved goals, compare performances in user ratings, or even compete with other users; to personalized training schedules, social sharing, or simply an interesting manner of presenting data and information. To communicate their topnotch features health app providers could present their app in best-selling health magazines such as Women's or Men's Health, or make use of market mavens. These could for instance, share the best qualities of the health app online and reach a broad audience of followers.

Finally, through stimulating social influence from friends and relatives all the above-mentioned qualities could be advertised. This can be accomplished for example by making a Facebook fan page and to generate awareness for the health-related smartphone app via advert optimization. Naturally, the power of word of mouth should not be underestimated and certainly leveraged. The best viral marketing for initial usage intention will be to hear about the health-related smartphone app from a friend or relatives themselves. In most cases however, this is only possible after the actual usage took place, which brings up the key question of how to keep the health app user engaged, and therefore, influence continuous usage intention.

User engagement is important for health behavior change and thus, for impacting public health positively. Although habit primarily indicates routinized behavior, there are a few techniques health app providers can utilize in order to reinforce habit. For instance, push notifications offer a great possibility to re-engage the user. Depending on the type of health app, these can include reminders, activities or news. Via deep-links, push notifications can direct the user to different in-app goals. By offering the user the chance to personalize these notifications, it adds value to the user experience, which consequently fosters continuous usage intention. A way in which health app providers can personalize its services is by gaining insights to user engagement. Through the collection and evaluation of user feedback (e.g. by means of app reviews, integrated feedback forms, or Social Media), health app providers can crowd source user opinions and re-target usage intention. This two-way communication between health app provider and user further build a close relationship and strengthens the trust in the app provider.

Concluding, health app providers should direct their efforts towards reinforcing continuous usage intention and thereby enhancing the link to initial usage intention (Venkatesh et al., 2012), which will close the cycle by targeting prospective users anew. A promising technique to emphasize all health app qualities important for usage intention is by presenting usage scenarios in advertisements. This is likely to re-engage users and activate initial usage intention among prospective users.

5.6. Limitations and Directions for Future Research

Naturally, this study has its limitations with respect to methodology, analysis and theoretical aspects. Firstly, it has to be acknowledged that this study investigates which factors determine the initial and continuous usage intention of health-related smartphone apps in general. However, there is one crucial step consumers have to undergo before the actual usage of an app; that is, the download the app in the corresponding app store of their smartphone operating system. Next to the factors predicting initial usage intention in this study, other factors like the information about an app, which a prospective user can find in the app store would additionally influence consumers' download intention. Such information includes the chart position, rating systems, customer reviews, description, screenshots, icons, other developer's app, new updates and many more. For instance, mobile marketing experts claim that popular health app providers can be recognized on the basis of a larger app portfolio, which reflects their experience in the market (Mroz, 2013; research2guidance, 2014). Also, a higher position of the app in the charts indicates a higher download rate, which in turn reflects the positive response from the general public (Mroz, 2013). Therefore, further research investigating which factors within Apple's app store or the Google Play store determine the actual health app choice after initial usage intention is welcomed. Furthermore, it has to be noted that this study focused on consumer health-related apps. Patient medical apps are still in its fits and starts and, compared to consumer health-related apps, hardly to find in the mobile market. It can be expected that medical apps will be primarily used on other mobile devices such as tablets for patient care monitoring, as these are primarily used at home (Kamps, 2015; Mroz, 2013). Further research is required in order to validate the results of current research findings in the medical context.

Another methodological restriction is the amount of respondents for both models. Although the unequal proportion of users and non-users of health-related apps in this study is a research finding in itself, it has to be noted that a real comparison between users and non-users in the Netherlands was not achievable. Hence, interpretations of this study have to be taken as an indication only. For a better reflection of reality researchers should aim for a longitudinal study, which measures the predicted factors among an equal amount of non-users and users over a certain period of time (Dooley, 2001).

Secondly, there are certain limitations to the research findings. First and foremost, partial least squares (PLS), a structural equation modeling technique (SEM), is advised for future research, as it helps to clarify models with many predictor variables (Field, 2009). Furthermore, the results are somewhat skewed as the mean ages for both participant groups range from 32 (users) to 40 (non-users). This means that especially among the users group, older populations are in the minority so that research findings should be interpreted with caution, as they cannot be generalized for the elderly.

Lastly, further research is needed in the domain of consumer health technology acceptance and usage. As Europe is facing rising health care costs due to ageing population and the treatment of chronic diseases, consumers, who will make use of medical health technologies are assumed to be individuals representing the elderly population (Wang et al., 2014). While developing the UTAUT 2, Venkatesh et al. (2012) discovered that age moderates the effect of all predictors on behavioral intention. Therefore, research investigating the moderating effect of age is needed in order to draw practical conclusion for the commercialization of medical apps.

Furthermore, following thoughts of the IS-continuance model (Bhattacherjee, 2001), investigating continuous usage intention of health-related and medical smartphone apps respectively should include elements of customer satisfaction. It can be imagined that people are more likely to continue using a mobile health device when they are satisfied with its usage. Future research should therefore, focus the hedonic and social gratifications of health app usage (Li Li, Liu, Xu, Heikkilä & Van der Heijden, 2015).

5.7. Outlook

Mobile health is just at the beginning of transforming the healthcare industry and it remains to be seen whether this niche market has the ability to fully revolutionize the healthcare sector. Yet, there are two developments to be expected. On the one hand, patient medical apps are foreseen to surpass the popularity of health and fitness apps (research2guidance,). Their integration into the healthcare system will improve the interaction between medical practitioners and patients, and thereby support healthcare institutions in providing services more efficiently and effective. In five years from now, it is likely that healthcare specialists will indeed become a major distribution channel of health apps, and that health insurance providers will cover mobile health usage. Hence, it is possible that health apps will be prescribed as a medical treatment. However, quite a few obstacles still have to be overcome and studies like these will help in investigating successful user adoption.

On the other hand, wearable devices and sensors will send off smartphones from being the number one target device for mobile health services (research2guidance). Instead, smartphones will become the center for all connected devices. Therefore, the ability to connect a health app to other gadgets will become a significant factor for health app usage intention. Already today, Apple and Microsoft have shown their progress in wearable technology with the Microsoft fitness band and the Apple Watch. Major players such as Apple, Google, Samsung, and Microsoft will rapidly progress in providing technological solutions that make mobile health accessible, and thereby use their brand power impacting public health positively. Despite their current limitations in offering functionalities for health services, wearables offer huge potential for the years to come.

References

Ahtinen, A., Mattila, E., Väätänen, A., Hynninen, L., Salminen, J., Koskinen, E., & Laine, K. (2009). User experiences of mobile wellness applications in health promotion: User study of wellness diary, mobile coach and selfrelax. Proceedings of the 3rd International ICST Conference on Pervasive Computing Technologies for Healthcare. doi: 10.4108/ICST.PERVASIVEHEALTH2009.6007.

Ajzen, I. (1991). The Theory Of Planned Behavior. *Organizational Behavior and Human Decision Processes, 50*, 179-211.

Akter, S., D'Ambra, J., and Ray, P. (2011). Trustworthiness in mHealth information services: An assessment of a hierarchical model with mediating and moderating effects using partial least squares (PLS). *Journal of the American Society for Information Science and Technology*, 62 (1), 100-116. doi: 10.1002/asi.21442.

Albrecht, U., Pramann, O. & Von Jan, U. (2014). Synopsis for Health Apps: Transparency for Trust and Decision Making. In M. Househ, E. Borycki & A. Kushniruk (Eds.), *Social media and mobile technologies for healthcare* (pp. 94-108). Hershey, PA: IGI Global.

App Annie. (2015). Insights into app engagement Q1 2015. Retrieved from https://s3.amazonaws.com/files.appannie.com/reports/Insights-Into-App-Engagement-Q1-2015-EN.pdf?mkt_tok=3RkMMJWWfF9wsRokv67LZKXonjHpfsX87OgrX6%2Bg38431UFwdcjKPmjr1YEISMN0aPyQAgobGp5I5FEITbHYTaVkt6cFXw%3D%3D

Ariaeinejad, R. & Archer, N. (2014). Importance of mobile technology in successful adoption and sustainability of chronic disease support system. *International Scholarly and Scientific Research & Innovation*, 8 (4), 870-875.

Avancha, S., Baxi, A., & Kotz, D. (2012). Privacy in mobile technology for personal healthcare. *ACM Computing Surveys, 45*(1), 1-54.

Babbie, E. (2009). *The practice of social research* (12th ed.). Wadsworth, Belmont, California: Cengage Learning.

Baron, R. & Kenny, D. (1986). The moderator-mediator variable distinction in social psychological research: Conceptual, strategic, and statistical considerations. *Journal of Personality and Social Psychology, 51*(6), 1173-1182.

Bender, M., Choi, J., Arai, S., Paul, S., Gonzalez, P., & Fukuoka, Y. (2014). Digital Technology Ownership, Usage, and Factors predicting downloading Health apps among Caucasian, Filipino, Korean, and Latino Americans: The Digital Link to Health Survey. *JMIR MHealth UHealth, 2*(4). Doi: 10.2196/mhealth.3710.

Bhattacherjee, A. (2001). Understanding information systems continuance: An expectation-confirmation model. *MIS Quarterly*, 25 (3), 351-370.

Boulos, M., Wheeler, S., Tavares, C., & Jones, R. (2011). How smartphones are changing the face of mobile and participatory healthcare: An overview, with example from eCAALYX. *BioMedical Engineering OnLine, 10*(24), 1-14.

Brown, S. A. & Venkatesh, V. (2005). Model of adoption of technology in households: A baseline model test and extension incorporating household life cycle. *MIS Quarterly*, 29 (3), 399-426.

Caburnay, C. A., Graff, K., Harris, J. K., McQueen, A., Smith, M., Fairchild, M. & Kreuter, M. W. (2015). Evaluating diabetes mobile applications for health literate designs and functionality, 2014. *Preventing Chronic Disease*, 12, E61. doi: 10.5888/pcd12.140433.

Chen, L., Meservy, T. O. & Gillenson, M. (2012). Understanding information systems continuance for information-oriented mobile applications. *Communications of the Associations for Information Systems*, 30 (9), 127-146.

Cheng, L., Mendonça, G., & Júnior, J. (2014). Physical activity in adolescents: Analysis of the social influence of parents and friends. *Jornal De Pediatria,90*(1), 35-41. doi: 10.1016/j.jped.2013.05.006.

Chong, A. Y. (2013). A two-staged SEM-neural network approach for understanding and predicting the determinants of m-commerce adoption. *Export Systems with Applications*, 40, 1240-1247. doi: 10.1016/j.eswa.2012.08.067.

Cortina, J. (1993). What is coefficient alpha? An examination of theory and applications. *Journal of Applied Psychology*, 78(1), 98-104.

Coulter, K. S. & Coulter, R. A. (2007). Distortion of price discount perceptions: The right digit effect. *Journal of Consumer Research*, 34 (2), 162-173.

Davis, F. D. & Venkatesh, V. (2004). Toward preprototype user acceptance testing of new information systems: Implications for software project management. *IEEE Transactions on Engineering Management*, 51 (1), 31-46. doi: 10.1109/TEM.2003.822468.

De Guinea, A. O. & Markus, M. L. (2009). Why break the habit of a lifetime? Rethinking the roles of intention, habit, and emotion in continuing information technology use. *MIS Quarterly*, 33 (3), 433-444.

De Veaux, R., Velleman, P., & Bock, D. (2014). *Stats Data and Models* (3rd ed.). Edinburgh Gate, Harlow, Essex: Pearson Education Limited.

Dehzad, F., Hilhorst, C., Bie, C., & Claassen, E. (2014). Adopting Health Apps, What's Hindering Doctors and Patients? *Health, 6*, 2204-2217.doi: 10.4236/health.2014.616256.

Disatnik, D., & Sivan, L. (2014). The multicollinearity illusion in moderated regression analysis. *Marketing Letters,* 1-6. doi: 10.1007/s11002-014-9339-5.

Dodds, W. B., Monroe, K. B., and Grewal, D. (1991). Effects of price, brand, and store information on buyers' product evaluations. *Journal of Marketing Research*, XXVIII, 307-319.

Dooley, D. (2001). *Social Research Methods* (4th ed.). Upper Saddle River, New Jersey: Prentice Hall.

El-Wajeeh, M., Galal-Edeen, G. H., and Mokhtar, H. (2014). Technology acceptance model for mobile health systems. *IOSR Journal of Mobile Computing & Application*, 1 (1), 21-33.

Escobar-Rodríguez, T. & Carvajal-Trujillo, E. (2014). Online purchasing tickets for low cost carriers: An application of the unified theory of acceptance and use of technology (UTAUT) model. *Tourism Management*, 43, 70-88. doi: 10.1016/j.tourman.2014.01.017.

Field, A. (2009). *Discovering Statistics Using SPSS* (3rd ed.). Sage Publications.

Finlay, K., Trafimow, D., & Jones, D. (1997). Predicting Health Behaviors From Attitudes and Subjective Norms: Between-Subjects and Within-Subjects Analyses. *Journal of Applied Social Psychology, 27*(22), 2015-2031.

Funk, C. (2013). *Mobile Softwareanwendungen (Apps) im Gesundheitsbereich. Entwicklung, Marktbetrachtung und Endverbrauchermeinung*. Stuttgart: Ibidem-Verlag.

Gass, R., & Seiter, J. (2014). *Persuasion. Social influence and compliance gaining* (5th ed.). Pearson.

Gefen, D., Karahanna, E., and Straub, D. W. (2003). Inexperience and experience with online stores: The importance of TAM and trust. *IEEE Transactions on Engineering Management*, 50 (3), 307-321. doi: 10.1109/TEM.2003.817277.

Geiselhart, E. (2015). Mobile Health: How to Drive the Next Wave of Innovation. Retrieved from http://www.mddionline.com/article/mobile-health-innovation-how-drive-next-wave-innovation

Handel, M. (2011). MHealth (Mobile Health)—Using Apps for Health and Wellness. *EXPLORE: The Journal of Science and Healing, 7*(4), 256-261.

Harpham, R. (2015). Consumer mHealth App or Regulated Medical Device? Retrieved from http://www.mddionline.com/blog/devicetalk/consumer-mhealth-app-or-regulated-medical-device-03-04-15

Hofstede, H. (2013, December 10). Mobiel gebruik in Nederland 2013. Retrieved from https://www.sterc.nl/nl/blog/mobiel/mobiel-gebruik-in-nederland-2013

Holbrook, M. B. & Hirschman, E. C. (1982). The experiential aspects of consumption: Consumer fantasies, feelings, and fun. *Journal of Consumer Research*, 9, 132-140.

Holden, R., & Karsh, B. (2010). The Technology Acceptance Model: Its Past And Its Future In Health Care. *Journal of Biomedical Informatics, 43*, 159-172. doi: 10.1016/j.jbi.2009.07.002.

Janz, N. K. & Becker, M. H. (1984). The health belief model: A decade later. *Health Education Quarterly*, 11 (1), 1-47.

Kamps, I. (2015). *Einstieg in Erfolgreiches Mobile Marketing: App Marketing – App Monetarisierung – Mobile Advertising*. München: CayadaPress.

Kijsanayotin, B., Pannarunothai, S., and Speedie, S. M. (2009). Factors influencing health information technology adoption in Thailand's community health centers: Applying the UTAUT model. *International Journal of Medical Informatics*, 78, 404-416. doi: 10.1016/j.ijmedinf.2008.12.005.

Kim, S. S. & Malhotra, N. K. (2005). A longitudinal model of continued IS use: An integrative view of four mechanisms underlying postadoption phenomena. *Management Science*, 51 (5), 741-755. doi: 10.1287/mnsc.1040.0326.

Kim, S. S., Malhotra, N. K., and Narasimhan, S. (2005). Two competing perspectives on automatic use: A theoretical and empirical comparison. *Information Systems Research*, 16 (4), 418-432. doi: 10.1287/isre.1050.0070.

Kim, S., Yoon, D., & Han, E. (2014). Antecedents of mobile app usage among smartphone users. *Journal of Marketing Communications,* 1-18. doi: 10.1080/135272662014.951065.

Klasnja, P., & Pratt, W. (2012). Healthcare in the pocket: Mapping the space of mobile-phone health interventions. *Journal of Biomedical Informatics,45*, 184-198. doi: 10.1016/j.jbi.2011.08.017.

Li, H., Liu, Y., Xu, X., Heikkilä, J., & Heijden, H. (2015). Modeling hedonic is continuance through the uses and gratifications theory: An empirical study in online games. *Computers in Human Behavior, 48*, 261-272. doi: 10.1016/j.chb.2015.01.053.

Limayem, M., Hirt, S. G., and Cheung, C. M. (2007). How habit limits the predictive power of intention: The case of information systems continuance. *MIS Quarterly*, 31 (4), 705-737.

Lober, W. B., & Flowers, J. L. (2011). Consumer empowerment in health care amid the Internet and Social Media. *Seminars in Oncology Nursing*, 27(3), 169-182. Doi: 10.1016/j.soncn.2011.04.002.

McPhilliamy, S. (2015). Opportunities for User Experience Innovation in Wearables. Retrieved from http://www.mddionline.com/blog/devicetalk/opportunities-user-experience-innovation-wearables-04-02-15

Meulendijk, M. C., Meulendijks, E. A., Jansen, P. A. F., Numans, M. E., & Spruit, M. R. (2014). What concerns users of medical apps? Exploring non-functional requirements of medical mobile applications. *Twenty Second European Conference on Information Systems*, Tel Aviv, 1-16.

Milne, S., Sheeran, P., and Orbell, S. (2000). Prediction and intervention in health-related behavior: A meta-analytic review of protection motivation theory. *Journal of Applied Social Psychology*, 30 (1), 106-143.

Milne, S., Orbell, S., and Sheeran, P. (2002). Combining motivational and volitional interventions to promote exercise participation: Protection motivation theory and implementation intentions. *British Journal of Health Psychology*, 7, 163-184.

Min, Q., Ji, S., and Qu, G. (2008). Mobile commerce user acceptance study in China: A revised UTAUT model. *Tsinghua Science and Technology*, 13 (3), 257-264.

Mroz, R. (2013). *App-Marketing für iPhone und Android: Planung, Konzeption, Vermarktung von Apps im Mobile Business* (1. Aufl. ed.). Heidelberg [u.a.]: Mitp.

Muzaffar, H., Chapman-Novakofski, K., Castelli, D., & Scherer, J. (2014). The HOT (Healthy Outcome for Teens) project. Using a web-based medium to influence attitude, subjective norm, perceived behavioral control and intention for obesity and type 2 diabetes prevention. *Appetite, 72*, 82-89. doi: 10.1016/j.appet.2013.09.024.

Norman, P. (1995). Health locus of control and health behavior: An investigation into the role of health value and behavior-specific efficacy beliefs. *Personality and Individual Differences*, 18 (2), 213-218.

O'Brien, R. (2007). A Caution Regarding Rules Of Thumb For Variance Inflation Factors. *Quality & Quantity, 41*, 673-690. doi: 10.1007/s11135-006-9018-6.

Oosterveer, D. (2013). Bijna driekwart van de Nederlanders bezit smartphone. Retrieved from http://www.marketingfacts.nl/berichten/bijna-driekwart-van-de-nederlanders-bezit-smartphone

Or, C. K. L., Karsh, B., Severtson, D. J., Burke, L. J., Brown, R. L., and Brennan, P. F. (2010). Factors affecting home care patients' acceptance of a web-based interactive self-management technology. *Journal of American Medical Informatics Association*, 1-9. doi: 10.1136/jamia.2010.007336.

Otto, R. (2014). Nederland in top-5 smartphone bezit. Retrieved from http://www.adformatie.nl/artikel/nederland-top-5-smartphone-bezit

Patrick, K., Griswold, W. G., Raab, F., & Intille, S. S. (2008). Health and the mobile phone. *American Journal of Preventive Medicine*, author manuscript.

Pavlou, P. A. (2003). Consumer acceptance of electronic commerce: Integrating trust and risks the technology acceptance model. *International Journal of Electronic Commerce*, 7 (3), 101-134.

PwC (2012[a)]). Emerging mHealth: Paths for growth. A global research study about the opportunities and challenges of mobile health from the perspective of patients, payers and providers. Retrieved from http://www.pwc.com/en_GX/gx/healthcare/mhealth/assets/pwc-emerging-mhealth-full.pdf

PwC (2012[b)]). Touching lives through mobile health. Assessment of the global market opportunity. Retrieved from http://www.pwc.in/assets/pdfs/telecom/gsma-pwc_mhealth_report.pdf

PwC (2013). Socio-economic impact of mHealth. An assessment report for the European Union. Retrieved from http://www.gsma.com/connectedliving/wp-content/uploads/2013/06/Socio-economic_impact-of-mHealth_EU_14062013V2.pdf

Raman, A. & Don, Y. (2013). Preservice teachers' acceptance of learning management software: An application of the UTAUT2 model. *International Education Studies*, 6 (7), 157-164. doi: 10.5539/ies.v6n7p157.

Research2guidance. (2014). mHealth app developer economics 2014. The state of the art of mHealth app publishing. Retrieved from http://research2guidance.com/r2g/research2guidance-mHealth-App-Developer-Economics-2014.pdf

Research2guidance. (2015). EU countries' mHealth app market ranking 2015. Which EU countries are best for doing mHealth business. Retrieved from http://research2guidance.com/r2g/research2guidance-EU-Country-mHealth-App-Market-Ranking-2015.pdf

Rosenstock, I. M., Strecher, V. J., and Becker, M. H. (1988). Social learning theory and the health belief model. *Health Education Quarterly*, 15 (2), 175-183.

Schwarzer, R. (2008). Modeling health behavior change: How to predict and modify the adoption and maintenance of health behaviors. *Applied Psychology: An International Review*, 57 (1), 1-29. doi: 10.1111/j.1464-0597.2007.00325.x.

Simons, L. P. A., Hampe, J. F., & Guldemond, N. A. (2013). ICT supported healthy lifestyle interventions: Design lessons. *Electron Markets*, 24, 179-192. doi: 10.1007/s12525-014-0157-7.

Slade, E. L., Williams, M. & Dwivedi, Y. (2013). An extension of the UTAUT 2 in a healthcare context. *UK Academy for Information Systems Conference Proceedings*. Paper 55.

Smith, B. N. & Stasson, M. F. (2000). A comparison of health behavior constructs: Social psychological predictors of AIDS-Preventive behavioral intentions. *Journal of Applied Social Psychology*, 30 (3), 443-462.

Su, W. (2014). A preliminary survey of knowledge discovery on smartphone applications (apps): Principles, techniques and research directions for E-health. *ICME International Conference on Complex Medical Engineering*, 369-374.

Sun, Y., Wang, N., Guo, X., and Peng, Z. (2013). Understanding the acceptance of mobile health services: A comparison and integration of alternative models. *Journal of Electronic Commerce Research*, 14 (2), 183-200.

Sweeney, J. C., Soutar, G. N., and Johnson, L. W. (1999). The role of perceived risk in the quality-value relationship: A study in a retail environment. *Journal of Retailing*, 75 (1), 77-105.

Tung, F., Chang, S., and Chou, C. (2008). An extension of trust and TAM model with IDT in the adoption of the electronic logistics information system in HIS in the medical industry. *International Journal of Medical Informatics*, 77, 324-335. doi: 10.1016/j.ijmedinf.2007.06.006.

Van der Heijden, H. (2004). User acceptance of hedonic information systems. *MIS Quarterly, 28*(4), 695-704.

Van Velsen, L., Beaujean, D., and van Gemert-Pijnen, J. (2013). Why mobile health app overload drives us crazy, and how to restore the sanity. *BMC Medical Informatics and Decision Making*, 13 (23), 1-5.

Venkatesh, V., Morris, M., Davis, G., & Davis, F. (2003). User acceptance of information technology: Toward a unified view. *MIS Quarterly, 27*(3), 425-478.

Venkatesh, V., Thong, J. Y. L., and Xu, X. (2012). Consumer acceptance and use of information technology: Extending the unified theory of acceptance and use of technology. *MIS Quarterly*, 36 (1), 157-178.

Verkasalo, H., López-Nicolás, C., Molina-Castillo, F. J., and Bouwman, H. (2010). Analysis of users and non-users of smartphone applications. *Telematics and Informatics*, 27, 242-255. doi: 10.1016/j.tele.2009.11.001.

Wang, B. R., Park, J., Chung, K., and Choi, I. Y. (2014). Influential factors of smart health users according to usage experience and intention to use. *Wireless Personal Communications, Springer*, 1-13. doi: 10.1007/s11277-014-1769-0.

Weber, K., Martin, M., & Corrigan, M. (2007). Real Donors, Real Consent: Testing the Theory of Reasoned Action on Organ Donor Consent. *Journal of Applied Social Psychology, 37*(10), 2435-2450.

West, D. (2012). How mobile devices are transforming healthcare. *Issues in Technology Innovation*, 18, 1-14.

West, J., Hall, P., Hanson, C., Barnes, M., Giraud-Carrier, C. & Barrett, J. (2012). There's an app for that: Content analysis of paid health and fitness apps. *Journal of Medical Internet Research*. 14(3). doi: 10.21.96/Jmir.1977.

Wilkowska, W., & Ziefle, M. (2011). Perception of privacy and security for acceptance of E-health technologies: Exploratory analysis for diverse user groups. *Pervasive Computing Technologies for Healthcare (PervasiveHealth) 5th International Conference,* 593-600.

World Health Organization. (1948). WHO definition of health. Retrieved from http://www.who.int/about/definition/en/print.html

Wu, I. & Chen, J. (2005). An extension of trust and TAM model with TPB in the initial adoption of on-line tax: An empirical study. *International Journal of Human-Computer Studies*, 62, 784-808. doi: 10.1016/j.ijhcs.2005.03.003.

Wu, C., Huang, Y., and Hsu, C. (2014). Benevolence trust: A key determinant of user continuance use of online social networks. *Information Systems and e-Business Management, Springer*, 12, 189-211. doi: 10.1007/s10257-013-0216-1.

York, R. (2012). Residualization is not the answer: Rethinking how to address multicollinearity. *Social Science Research, 41*, 1379-1386. doi: 10.1016/j.ssresearch.2012.05.014.

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

Zeithaml, V. A. (1988). Consumer perceptions of price, quality, and value: A means-end model and synthesis of evidence. *Journal of Marketing*, 52, 2-22.

Zevnik, T. [HIMSS SoCal]. (2012). Goin' mobile: Privacy and security implications of the mHealth revolution. [Video file]. Retrieved from http://www.youtube.com/watch?v=C4d0naBwF6g

Zhou, T., Lu, Y., and Wang, B. (2010). Integrating TTF and UTAUT to explain mobile banking user adoption. *Computers in Human Behavior*, 26, 760-767. doi: 10.1016/j.chb.2010.01.013.

Appendix

Table 15

Collineary statistics for the factors predicting initial and continuous usage intention of health-related smartphone apps

		Collinearity Statistics			
		Non-users Model		Users Model	
Dependent Variable	IV's	Tolerance	VIF	Tolerance	VIF
Performance Expectancy (PE)	EE	.540	1.851	.506	1.976
	SIfr	.663	1.508	.651	1.536
	SIsp	.579	1.728	.589	1.697
	FC	.486	2.056	.563	1.776
	HM	.511	1.958	.782	1.279
	PV	.601	1.664		
	HAB			.779	1.284
	TRU	.714	1.400	.819	1.221
	PPR	.885	1.130	.836	1.196
	VH	.676	1.478	.821	1.219
Effort Expectancy (EE)	PE	.465	2.151	.630	1.587
	SIfr	.613	1.632	.635	1.574
	SIsp	.557	1.796	.628	1.591
	FC	.682	1.467	.711	1.406
	HM	.471	2.121	.787	1.271
	PV	.587	1.705		
	HAB			.647	1.546
	TRU	.710	1.408	.804	1.244
	PPR	.885	1.130	.857	1.166
	VH	.465	1.470	.807	1.239
Social Influence: Friends and relatives (SIfr)	PE	.503	1.987	.637	1.570
	EE	.541	1.850	.499	2.003
	SIsp	.621	1.610	.720	1.388
	FC	.488	2.048	.562	1.780
	HM	.460	2.175	.808	1.238
	PV	.590	1.695		
	HAB			.635	1.574
	TRU	.706	1.416	.807	1.240
	PPR	.888	1.126	.839	1.191
	VH	.675	1.481	.809	1.236
Social Influence: Healthcare specialists (SIsp)	PE	.483	2.071	.620	1.612
	EE	.540	1.851	.531	1.882
	SIfr	.683	1.464	.775	1.290
	FC	.500	1.999	.563	1.776
	HM	.460	2.174	.784	1.276
	PV	.600	1.666		
	HAB			.655	1.526
	TRU	.707	1.415	.809	1.236
	PPR	.889	1.124	.834	1.199
	VH	.677	1.477	.806	1.240
Facilitating Conditions (FC)	PE	.468	2.139	.620	1.613
	EE	.762	1.313	.629	1.590
	SIfr	.619	1.616	.632	1.582
	SIsp	.576	1.736	.589	1.698
	HM	.460	2.173	.777	1.287

	PV	.593	1.686		
	HAB			.640	1.564
	TRU	.706	1.416	.815	1.277
	PPR	.931	1.074	.834	1.199
	VH	.738	1.355	.839	1.192
Hedonic Motivation (HM)	PE	.516	1.936	.626	1.598
	EE	.554	1.805	.506	1.977
	SIfr	.613	1.632	.660	1.514
	SIsp	.557	1.794	.596	1.679
	FC	.484	2.066	.565	1.770
	PV	.641	1.561		
	HAB			.680	1.470
	TRU	.764	1.308	.803	1.246
	PPR	.885	1.130	.831	1.203
	VH	.688	1.454	.818	1.223
Price Value (PV)	PE	.476	2.099		
	EE	.540	1.850		
	SIfr	.616	1.622		
	SIsp	.570	1.753		
	FC	.489	2.044		
	HM	.502	1.991		
	HAB				
	TRU	.718	1.393		
	PPR	.890	1.124		
	VH	.672	1.489		
Habit (HAB)	PE			.758	1.319
	EE			.506	1.977
	SIfr			.632	1.582
	SIsp			.606	1.650
	FC			.566	1.768
	HM			.828	1.208
	PV				
	TRU			.805	1.243
	PPR			.838	1.193
	VH			.806	1.241
Trust in App Provider (TRU)	PE	.470	2.128	.635	1.576
	EE	.543	1.841	.500	2.000
	SIfr	.613	1.633	.638	1.567
	SIsp	.557	1.794	.595	1.680
	FC	.483	2.068	.573	1.745
	HM	.498	2.010	.777	1.288
	PV	.596	1.679	.640	1.563
	HAB				
	PPR	.885	1.130	.848	1.180
	VH	.672	1.488	.814	1.228
Perceived Privacy Risk (PPR)	PE	.465	2.151	.622	1.234
	EE	.540	1.850	.512	1.606
	SIfr	.615	1.625	.638	1.951
	SIsp	.560	1.786	.589	1.566
	FC	.509	1.965	.564	1.697
	HM	.460	2.175	.773	1.774
	PV	.590	1.696		
	HAB			.640	1.294
	TRU	.706	1.416	.815	1.562

	VH	.720	1.389	.810	1.227
Valuation of Health (VH)	PE	.468	2.136	.630	1.587
	EE	.547	1.827	.498	2.010
	SIfr	.616	1.624	.635	1.575
	SIsp	.562	1.781	.588	1.701
	FC	.531	1.882	.585	1.709
	HM	.471	2.124	.784	1.275
	PV	.586	1.706		
	HAB			.635	1.574
	TRU	.707	1.415	.807	1.239
	PPR	.948	1.054	.836	1.196