Customers' Technology Acceptance of Mobile Applications for Personalized Healthcare

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In line with the global trend towards mobile technologies and the increased interest in personalized healthcare solutions various mobile applications for personalized healthcare have been created. The acceptance rate is lower than accepted and existing academic research reveals the need for further examination of the factors motivating people to use such applications. The present study, based on the Extended Unified Theory of Acceptance and Use of Technology (UTAUT2) model, examines the extent of the influence of price value, social influence, hedonic motivation and performance expectancy on the behavioural intention of end customers to use mobile health applications. The moderating factors age, gender and experience are also assessed. A survey was conducted among 123 residents of Bulgaria, aged 18-50, who are actively using smart phones. The researcher discovered that performance expectancy, followed by hedonic motivation, are the factors with the strongest influence on the individuals' decision to use mobile health applications.

Keywords
acceptance, customers, health, mobile applications, UTAUT2

1. Introduction

The usage of mobile technologies in healthcare has been growing in recent years. Thousands of commercial applications aiming to improve health have been developed. Although quite a recent development, self-monitoring is becoming a growing part of people's lifestyles [1], enabling individuals to take preventive measures for their health. Additionally, due to the increased costs associated with monitoring one's health, the adoption of mobile health technologies is considered unavoidable [2]. Investigating user perception and attitude toward a new technology at an early stage greatly contributes to its success [3]. Technology acceptance theories are applied in the field of mobile health technologies to predict the factors influencing customers to accept new health technologies. Despite the numerous available mobile health applications, adoption is not massive [2]. Further research is needed into the predictors of acceptance of mobile health applications [4]. Both from a theoretical and managerial perspective there is a need to study the ways value is created in advanced mobile services [5]. The expectations are that mobile health applications will become a profitable innovation [6]. Several factors influencing users' attitudes towards mobile health applications have been identified by academics as needing further examination. Therefore, in order to complement the existing knowledge, the present research will examine Price Value [7], Social Influence [4], Hedonic Motivation [8] and Performance Expectancy [9] and the extent of their influence on the Behavioural Intention of people to use mobile health applications. Results of technology acceptance research may vary among different cultures and markets [5]. Venkatesh [10] suggests that the UTAUT2 model should be tested in different countries and with different technologies. As there is little examination of the use of smartphone health apps in Bulgaria, this is also one of the aims of the present research, which was conducted among residents of Bulgaria.

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2. Literature Review

2.1 Technology Acceptance Theories

The literature review is based on articles related to technology acceptance theories and mobile applications for personalized healthcare. The Technology Acceptance Model, proposed by Fred Davis in 1989 [11], is one of the most widely-used model to explain technology usage. Initially, it was created due to the concern over workers not utilizing the technologies provided at their disposal. It was concluded that first acceptance had to be measured by asking the individuals about their intentions to use the specific technology. Then, when the factors impacting usage intentions were known, organizations could manoeuvre, manipulating those factors, stimulating acceptance and increasing usage [11-12]. Davis established that the factors influencing the Behavioural intention (BI) of users to accept new technologies are perceived usefulness (PU) and perceived ease of use (PEOU). Perceived usefulness refers to the belief of a person that using a system will enhance his or her job performance. Perceived ease of use reflects the degree to which person believes that using a system will require no effort [11].

Technology Acceptance Model (TAM) postulates that Behavioural Intention is the main acceptance determinant and any other variables influencing behaviour do so indirectly by influencing Behavioural Intention [12]. It should be noted that the intended usage (the behavioural intention) may slightly differ from the actual system usage. However, acceptance theories state that this deviation is not significant and that the process of acceptance can be predicted. Venkatesh and Davis [13] revised TAM and proposed an extended model. In 2008 Venkatesh and Bala [14] incorporated this model of determinants of perceived ease of use and proposed an integrated model, TAM3. Furthermore, Venkatesh designed a new model in 2003 [15] called Unified Theory of Acceptance and Use of Technology (UTAUT). The constructs in this new model are effort expectancy, performance expectancy, social influence and facilitating conditions. Identified are four moderating variables: gender, experience, age and voluntariness of use. Venkatesh defines performance expectancy as the person's belief that using a system will be helpful in his or her job performance. Effort expectancy is the perception of a person as to whether using a system will be difficult or easy. Social influence refers to a person's expectation of whether people who are important to him or her will expect them to use the system or not. The term facilitating conditions refers to the belief of a person as to whether the technical infrastructure exists to enable him or her to use the system.

Venkatesh [10] extends the UTAUT model to study the behavioural intention of consumers to accept a technology. The UTAUT2 constructs are most suitable for consumer use context. Three new constructs are introduced to the existing UTAUT model: hedonic motivation, price value and habit. Hedonic motivation is defined as the fun or pleasure derived from using a technology. Price value refers to the cost and pricing structure which may have a significant impact on consumers' technology use. Habit is the third factor introduced which influences the intention of consumers to use technology. The moderating factors gender, age and experience also bear implications and a recommendation made to business managers is to use market segmentation strategy to facilitate consumers' use of technology [10]. It should be noted that in the UTAUT2 model Venkatesh defines performance expectancy as the degree to which using a technology will provide benefits to consumers in performing certain activities not limited to his or her job, which was the case in the definition elaborated within the UTAUT model. Within the personal and voluntary context of mHealth, performance expectancy is perceived as the degree to which individuals believe that mHealth applications will help them attain gains in overall self-performance [16].

2.2 Mobile Applications for Personalized Healthcare

The studies investigating users' attitudes towards health information technology mostly focus on the perspective of physicians [17]. Such studies [18-19] research the factors influencing health professionals' behavioural intention. In contrast, the studies of patients' and customers' adoption of heath technologies are relatively rare. Multiple mobile applications have been created to assist people with managing stress, improving mood, following a healthy diet, increasing physical activity, quitting smoking, and self-managing chronic health problems. Some examples are visible in Figure 1 below. The applications provide information, advice, instructions, prompts, support, encouragement, and interactive tools for individuals to monitor, record, and reflect [20]. Men's Health magazine, one of the leading magazines influencing the way men behave and think about health [21], has published charts with the ten best applications for overall health and states that these applications are a good way to follow a healthy regime, stay motivated and track nutrition, improve mental acuity, follow one’s sleep cycle, stay fit and manage stress levels [22]. Despite the growing research in smartphone health applications, user acceptability issues present an area for further academic investigation and analysis [23]. Within the field of mental health, the meditation application Calm is a good example of a successful mobile health application. Business Insider news website [24] proclaims that since the application start-up was launched in 2012 it had reached a valuation of 1 billion USD by 2019. Another example of a successful business offering a mobile health application is the meditation app Headspace, with annual revenue worth $50 million and a valuation of about $250 million, as estimated by Forbes [25].

Figure 1. Health applications (from Apple App Store).

Cocosila and Archer [7] carried out an experiment in order to research users’ acceptance and the conclusion is that the extrinsic motivation (the perception of usefulness) of the participants in their survey – who were young (24 years old on average) and healthy people – came up as insignificant as these participants did not perceive mobile health applications as a useful preventive health tool. Making applications attractive and enjoyable, however, can comprise a key factor for the adoption of these health applications among younger people. Anderson [1] performed a qualitative research by conducting semi-structured interviews among young people and similarly concluded that incorporating gamification in health applications is an area requiring supplementary research. Gamification might be one of the methods boosting users’ engagement, though it needs further investigation [1,8]. A large proportion of the participants in a national survey in the United States indicated that they would not pay anything for health applications [26]. Birkhoff and Smeltzer [9] recognize the growing interest in user-centred mobile health tracking applications and point out the need for deeper understanding of the users’ motivation to continuously use health applications. They also observe that because of the novelty of user-centred mobile health tracking applications there is little data on the economic impact of these applications and more research is needed to evaluate the economic cost and benefits of utilizing these applications.

The perceived benefits of using health applications include greater self-awareness of one’s health condition, easier self-management in daily life, the ability to send data to health professionals without repeated visits, the ability to review historical data without consulting a doctor and social motivation to improve fitness [1]. The research conducted by Lim [27] – considered by Cho [28] as a path-breaking study in the mobile applications acceptance – applied the technology acceptance model (TAM) to assess Singaporean women’s adoption of smartphone apps for health information. The study established that perceived usefulness and self-efficacy positively predict the intention to use mobile health apps. In contrast to the obvious benefits of health applications, however, consumers’ perception of their usefulness is under question and the effectiveness and efficacy of smartphone-delivered self-help interventions is an area requiring further research [8]. Birkhoff and Smeltzer [9] agree that the usefulness of health applications features needs to be periodically examined. Also, social influence as a factor of acceptance needs further examination [28]. The role of social influence on the use of advanced mobile services has been underestimated, as the opinions of friends and family has been shown to have a significant impact on the decision of a person to adopt a new technology [5]. Effort expectancy and facilitating conditions in the study of Yuan [4] were not found to significantly influence behavioural intent. This is explained by the advancement of smartphone interfaces and usability, which reduces the needed amount of effort for usage. Privacy and data security are much valued by individuals in respect to mobile health applications [1] and fear of thread to privacy could potentially be a deterrent to usage [7]. Concerns over how stored information might be used by third parties, like advertisers and insurance companies, might prevent individuals from sharing information over mobile applications [29].

3. Methodology

3.1 Research Approach

A quantitative research design was adopted to reach the research aim and objectives, which entail a deductive research approach, and adopts a research philosophy of positivism, as the author’s objectively performs the research and reflects on its results. Quantitative data are collected through a survey, using paper self-administered questionnaires. An informed consent form preceded the questionnaires, to make the participants aware that the questionnaire is anonymous and confidential and that their participation is voluntary. Only individuals who agreed to the consent statement and signed the hard copy consent form participated in the survey and completed the questionnaire. The self-administered questionnaire was pre-tested on five individuals from the selected sample who confirmed that the questions were clear, that there were no contradictions, vague or misleading questions and that instructions were straightforward. They also observed that the questionnaire would not be offensive to any of the participants.

3.2 Sampling

The research is focused on the acceptance of mobile applications for personal healthcare. Subjects of this research are individuals owning a smartphone. Purposive non-probability homogenous sampling is used, due to the lack of a sampling frame. The participants were selected from the author’s work, a financial technologies company, and the surveys were distributed at the office premises. The participants are professionals of different occupations, aged between 20 and 50 years, male and female, exposed to and experienced in technology, with medium or high financial income, residents of Sofia, Bulgaria. It should be noted that some existing academic research shows that individuals with higher education and higher financial income represent the group which is most likely to purchase mobile health applications [26, 30].

3.3 Data Collection Tool

The individuals were asked about their behavioural intention to use mobile health applications, whether they find them useful, about their opinion on the price of such applications, whether they perceive them as entertaining and whether they take into consideration the feelings of their friends and family about mobile health applications. All participants owned a smartphone and some were using health applications while others were not. The questionnaire contains constructs from UTAUT2, and the questions are adopted from the survey items proposed in the article by Venkatesh [10] on an extended version of UTAUT, slightly adapted to comply with the mobile health context. The questionnaire was created in the English language as all individuals from the sample are completely fluent in English. The items were measured on a 5-point Likert-type scale, ranging from 1=strongly disagree to 5=strongly agree. The questionnaire contained the images from Figure 1, referring the participants to mobile applications for personal healthcare, for example tracking steps, water intake and quality of sleep.

3.4 Research Model and Hypotheses

The current research is based on the UTAUT2 model and the constructs under examination are Price Value (PV), Social Influence (SI), Hedonic Motivation (HM) and Performance Expectancy (PE) as determinants of Behavioural Intention (BI). The following hypotheses are examined:

H1: Price Value has a positive effect on the behavioural intention of using mobile applications for personalized healthcare.

The need to further examine price value as a determinant of mobile health applications acceptance is stated in Cocosila and Archer [7] and in Birkhoff and Smeltzer [9].

H2: Social Influence has a positive effect on the behavioural intention of using mobile applications for personalized healthcare.

A gap is recognized in the study of social influence as a factor motivating consumers to use mobile health technologies in Cho [28] and in Yuan [4].

H3: Hedonic Motivation has a positive effect on the behavioural intention of using mobile applications for personalized healthcare.

The feeling of entertainment as a driver to use health applications is an under-researched field according to Anderson [1] and Juarascio [8].

H4: Performance Expectancy has a positive effect on the behavioural intention of using mobile applications for personalized healthcare.

The need for further research into the perception of usefulness as a factor is emphasized by Juarascio [8], Birkhoff and Smeltzer [9] and El-Wajeeh [31].

4. Data Analysis and Results

4.1 Respondents Profile

The IBM SPSS (statistics version 24) statistical tool was used to analyse the collected quantitative data. First, the profile of the respondents was analysed, taking into consideration their age, gender and profession. It was established that there was almost an equal number of members from each gender. Such an almost equal distribution is good for an analysis unbiased by a predominant number in one gender. Regarding the age of the participants 9.8% were in the age range of 18-25 years, 61.5% were in the range of 26-35 years, 25.4% were in the range of 36-45 years and 3.3% were in the range of 46-50. The respondents had various occupations, the majority of them being Software Developers (23%).

4.2 Assessing Normality

As part of the preliminary statistics, the normality of the data was assessed by observing the skewness and kurtosis of the data and descriptive statistics was run. The analysis of the data shows that only the scale measuring the experience with browsing websites is significantly skewed and kurtotic with values much above the threshold of 1.96. However this does not indicate a problem with the scale, but it reflects a tendency in the measured construct. The values of the rest of the items indicate normal distribution. Descriptive statistics was run for the four moderating variables measuring experience. The mean scores indicate that the respondents browse websites, use mobile email and social media frequently, every day to many times a day, whereas they download applications occasionally or on some days (mean score 2.80).

4.3 Reliability Analysis

Reliability analysis is run to confirm that the items which make up each scale measure the same underlying construct. The internal consistency of all scales has been confirmed by the results of the reliability analysis as the coefficient of Cronbach's Alpha obtains a value greater than .7 for each scale.

4.4 Correlation Analysis

Correlation analysis is run to examine the strength and direction of the linear relationship between the dependent variable Behavioural Intention (BI) and the independent variables Price Value (PV), Social Influence (SI), Hedonic Motivation (HM) and Performance Expectancy (PE). Pearson product-moment correlation coefficient shows strong positive correlation between BI and the independent variables HM (r = .573), and PE (r = .748) and positive correlation with medium strength between BI and the variables SI (r = .445), PV (r = .417). The results are depicted in Table 1 below. The value of the significance level is below .05 which indicates that the specific study can have confidence in the obtained results. The author's calculated the coefficient of determination, which reveals how much variance the pairs (dependent and independent) of variables share. Performance Expectancy helps to explain nearly 56% of the variance in the respondents' scores on the Behavioural Intention scale. There might be differences in the mobile health applications acceptance between males and females [1]. Due to that reason we decided to run correlation analysis, examining the relationship between the dependent variable Behavioural Intention and each independent variable for males and females separately. The output showed no statistically significant difference between the two correlation coefficients for the genders.

Table 1. Correlations

		1.	2.	3.	4.	5.
1. Behavioral Intention	Pearson Correlation	1	.417	.445	.573	.748
	Sig. (1-tailed)		0.000	0.000	0.000	0.000
	N	122	122	122	122	122
2. Price Value	Pearson Correlation	.417	1	.281	.435	.494
	Sig. (1-tailed)	0.000		0.001	0.000	0.000
	N	122	122	122	122	122
3. Social Influence	Pearson Correlation	.445	.281	1	.436	.485
	Sig. (1-tailed)	0.000	0.001		0.000	0.000
	N	122	122	122	122	122
4. Hedonic Motivation	Pearson Correlation	.573	.435	.436	1	.621
	Sig. (1-tailed)	0.000	0.000	0.000		0.000
	N	122	122	122	122	122
5.Performance Expectancy	Pearson Correlation	.748	.494	.485	.621	1
	Sig. (1-tailed)	0.000	0.000	0.000	0.000	
	N	122	122	122	122	122

4.5 Standard Multiple Regression

In addition, multiple regression analysis was performed to explore the predictive ability of the independent variables on the dependent one and to check the influence of the moderating variables. We evaluated the model by first checking the R Square which indicated that the examined independent variables explain 58.4% of the variance in the behavioural intention of the sample to use mobile health applications. The Sig. value from the ANOVA table is .000 which indicates the statistical significance of the model. The author's also examined the standard coefficients and Sig. values to examine the amount and significance of the contribution of each variable to the prediction of the dependent variable. The values show that Performance Expectancy has the strongest unique contribution to explaining Behavioural Intention (Beta Value is .60 and Sig. is 0.00). Hedonic Motivation (Beta 0.152, Sig. 0.057) is found to have only mild significance. Price Value (Beta 0.032, Sig. 0.643) and Social Influence (Beta 0.078, Sig. 0.261) were not found to have strong predictive abilities for Behavioural Intention. The part correlation coefficient shows that Performance Expectancy explains 18% of the variance in the Behavioural Intention scores.

4.6 Hierarchical Multiple Regression

Downloading Applications, Browsing Websites and Using Mobile Email were assessed as a proxy for experience. They were used as moderators to maintain consistency with the way the UTAUT2 model is formulated. The values of R Square indicate that the variables in Model 1, (Model 1 includes the moderating variables Age Groups, Gender, Social Media, Downloading Applications, Browsing Websites, Mobile Email) explain 5.7% of the variance. The R Square value of Model 2, (Model 2 contains all independent and all moderating variables), shows that the model as a whole explains 61.2% of the variance. The value of R Square Change indicates that the independent variables PV, HM, SI and PE explain an additional 55.6% of the variance of behavioural intention after the effect of the variables from Model 1 is removed. The Sig. F Change value (.000) indicates that this is a statistically significant contribution. The ANOVA table indicates that the model as a whole (including both blocks of variables) is significant (Sig. value is .000). The Coefficients table displays how well each of the variables contributes to the final equation. The Sig. values are below the cut-off of 0.5 for the Age Groups (sig. 0.036) and for Performance Expectancy (Sig. 0.00), which means that they make a statistically significant contribution. Their Beta values indicate that their unique contribution to the variance of Behavioural Intention for this sample is 14% for Age and 65% for Performance Expectancy, when the overlapping effects of all other variables are statistically removed. The Sig. value of Hedonic Motivation (Sig. 0.068) indicates mild significance and unique contribution of 15%.

5. Conclusions

5.1 Discussion of Findings

The correlations analysis, shows that all correlations are statistically significant and in the expected direction, according to the UTAU2 theoretical model. A multiple regression analysis was used to assess the predictors of smartphone health applications. The analysis showed that the current model explained 61.2% of the variance ($R^2 = 0.612$), which is comparable to the health and fitness apps adoption study based on UTAU2 by Yuan [4], whose model result is $R^2 = 0.63$. The authors also explored the moderators gender, age and experience and found no statistically significant moderation effect. The results of the analysis show that performance expectancy is an antecedent to behavioural intention (r = .748, Beta = .60, Sig. = 0.00) with 65% unique contribution to the variance. This result is compliant with other existing academic studies on mobile health applications which show that the construct performance expectancy positively and significantly affects an individual’s behavioural intention to use health apps [4, 6, 27, 28, 32]. Hedonic motivation was found to have mild statistical significance on the behavioural intention variance (r = .573, Beta = 0.152, Sig. = 0.057). This result is comparable with the findings of Yuan [4]. Although social influence (r = .445, Beta = 0.078, Sig. = 0.261) and price value (r = .417, Beta = 0.032, Sig. = 0.643) are found to be positively associated with behavioural intention, the findings of the present research show that their relationships are not statistically significant.

A recent UTAUT2-based study by Duarte and Pinho [2] shows that performance expectancy and hedonic motivation are strong predictors of mHealth adoption, which is in line with the findings of the present study. This means that the perception of usefulness of the mobile health applications is critical to new adopters. Performance expectancy is undoubtedly a key factor in mobile health applications acceptance, as this result is supported by the findings of other recent studies as well [32-33], with which the present work is consistent. Duarte and Pinho [2] conclude that there is no single condition which can exclusively explain mHealth adoption, although performance expectancy is the best predictor. Combined with hedonic motivation, the two factors represent necessary conditions for mHealth adoption, a fact which has to be acknowledged by market players and decision makers in the field. Hedonic motivation, in contrast to the findings of the present study and other existing research in the field [2], is not found to be a significant factor in the adoption behaviour of citizens of the United States and Canada in the research conducted by Dwivedi [16]. Among Bangladeshi citizens, however, the same research indicates that hedonic motivation is a strong determinant. Dwivedi [16] concludes that the findings indicate that cultural differences have a decisive impact on adoption behaviour. The present study found mild significance of this construct. This is similar to recent research which found the hedonic factor to be motivating for some people but not critical for usage decision [29].

5.2 Validation of Hypotheses

H1: Price Value has a positive effect on the behavioural intention of using mobile applications for personalized healthcare.

This hypothesis was not supported by the data. Price value is positively associated with behavioural intention. Their relationship, however, is not statistically significant.

H2: Social Influence has a positive effect on the behavioural intention of using mobile applications for personalized healthcare.

This hypothesis was not supported by the data. Although social influence is positively associated with behavioural intention, the relationship is not statistically significant.

H3: Hedonic Motivation has a positive effect on the behavioural intention of using mobile applications for personalized healthcare.

The results showed only mild statistical significance in the contribution of the hedonic motivation to the variance of the behavioural intention.

H4: Performance Expectancy has a positive effect on the behavioural intention of using mobile applications for personalized healthcare.

The results supported this hypothesis as performance expectancy was found to be a strong determinant of behavioural intention.

5.3 Research Implications

MHealth should be seen as the future of healthcare, as it has the capacity to make the service better in quality, faster, less expensive, and predominantly focused on the customer [2]. The main findings of this research are that performance expectancy is a strong determinant of customers' intention to accept a mobile health application, followed by hedonic motivation. For the practitioners concerned with fostering mHealth adoption, it is important to adopt an integrated approach centred on performance expectancy [2] and hedonic motivation. All features, interface and marketing endeavours should be directed towards the usefulness of the application. Customers should be made aware that mobile health applications can really help them monitor and improve their health and reach their health goals. The participants in the study found hedonic values to be somewhat important. Therefore, when designing the apps, some entertaining features should be involved, to keep users involved and engaged. Some gamification and fun elements can be included. The interface should be appealing. Relevant marketing campaigns can indicate that using the app is fun and entertaining. The present study will be of use to all stakeholders such as service providers, software developers, marketing experts, graphic designers, business entrepreneurs, policy makers, business managers as well as academics striving to understand what drives people to use mobile health applications.

5.4 Limitations and Future Research Directions

Considering time and budget constraints as well as available access the author’s conducted the research among professionals, colleagues of one of the author’s, aged 18-50 (most in the 26-35 age group), all with higher education and higher incomes. Therefore, the findings cannot be generalised, and this is one of the disadvantages of the present research. A future research with a larger and more versatile sample would be recommendable. Nevertheless, with its sample of 122 individuals, originality in cultural and geographical context, and a thorough statistical analysis with statistically significant constructs, the study represents a contribution to the existing knowledge in the domain. The study performed a quantitative study focused on the UTAUT2 constructs in examining individuals’ acceptance of mobile health applications. Future work can focus on qualitative methods in examining users’ acceptance and on testing the practicability of health applications to define the requirements essential for their high adoption [26]. Technology use between healthy individuals and patients may vary [34]. The present study aims to examine the acceptance of mobile applications for personal health in their full range, not limited to a particular health condition. It should also be noted that only voluntary usage of the mobile health applications was studied and that results may differ in mandatory settings [5, 35].

The study examined four UTAUT2 constructs in the context of mobile health applications and the results show that performance expectancy and hedonic motivation are determinants of customers’ intention to use smartphone applications for personal healthcare. Further research in the domain is needed. The model of UTAUT2 can be adopted in future similar studies. Other models can also be adopted to enrich the theoretical framework of technology acceptance of mobile applications for personal healthcare.

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