Increasing mobile health applications usage among Generation Z members: Evidence from the UTAUT model

Purpose: The acceptance of mobile health (m-health) applications, especially those of a preventive nature, by individuals, is not well understood. Despite the benefits offered by m-health applications in improving and sustaining health and well-being through various avenues, widespread adoption is yet to be seen. Within this context, this study aims to reveal the enabling factors and barriers that influence the use of m-health applications among Generation Z.

Methodology: The Unified Theory of Acceptance and Use of Technology (UTAUT) was extended with e-health literacy, trust, and enjoyment constructs. Data from a survey study on 312 Generation Z members were analysed via structural equation modelling, shedding light on the reasons why new generations adopt mobile health apps.

Findings: The findings indicate that social influence and enjoyment are the most significant factors influencing the use of m-health apps. The significant impact of performance and effort expectancy on intentions was also confirmed by the results. Moreover, privacy risk was identified as a barrier to adoption. The results also indicated that the strong influence of trust on privacy risk can be used to offset those privacy concerns.

Practical implications: The findings highlight that hedonic motivation, which is commonly overlooked in health settings, plays an important role in m-health app use. Thus, promoting mobile app features that provide enjoyment will be influential in attracting the younger generation.

Originality/value: The context of the study differs from the norm and focuses on a regional health tourism hub, Turkey, situated at the crossroads of Europe and Asia. UTAUT model is modified with relevant constructs, namely enjoyment, e-health literacy and privacy risk, to better fit the m-health context.

Keywords: mobile applications; mobile health; mhealth; e-health; digital health; UTAUT

Introduction

Ageing populations in both developed and developing countries are fuelling a steady increase in healthcare costs. The Covid-19 pandemic has exposed the fragility of health systems that were already struggling to cope with an increasing number of chronic medical conditions (Agnihothri et al., 2020; Worrall & Chaussalet, 2015). Sedentary behaviour, unhealthy eating habits, and substance abuse (including drugs, tobacco, and alcohol) are all contributing to the rise of chronic medical conditions such as diabetes, obesity, and hypertension leading to poor public health outcomes (World Health Organization, 2014). Within this context, the effective use of technology and mobile devices emerges as a promising tool for cost-effective preventive measures that can shift the focus of healthcare toward being more citizen/patient-centric (Bettiga et al., 2020; Helbostad et al., 2017; Osei-Frimpong et al., 2018) and be instrumental in decreasing the burden on health systems. M-health has the potential to contribute to public health systems in numerous ways, such as preventing adverse health conditions and diseases before they occur (i.e. preventive medicine/health) through promoting healthy eating, an active lifestyle, increased awareness and health literacy, and improved mental health.

Despite growing popularity, which is partly attributable to the Covid-19 pandemic, a larger proportion of the general population is yet to embrace m-health applications (Ceci, 2022; Phaneuf, 2020). In particular, the younger generation, despite being digitally savvy, may not see the need to use preventive health-related apps due to their good health conditions. However, adopting a healthy lifestyle at an early age facilitated by m-health apps is a promising means of preventive medicine, considering that unhealthy habits are difficult to change at later ages. For example, Generation Z (Gen-Z) member students in Turkey in particular are viable targets of m-health apps given their relatively low scores in healthy eating habits and physical activity (e.g. Kara, 2014). This may fuel their interest in apps that facilitate healthy eating and promote physical activity. Additionally, considering the variety of mobile applications ranging from ones that aim to improve sexual health via tackling empowerment, education and prevention around sexuality (e.g. managing menstrual cycle, birth control reminders, learning about safe sex, sexual self-care, etc.) to limiting the use of or quitting alcohol, tobacco products make Gen-Z members viable targets of such applications (Gannon *et al.*, 2020; Richman *et al.*, 2014).

Enabling healthy lifestyles at an early age can contribute to sustainable health systems. Therefore, policymakers, healthcare organisations, and relevant stakeholders should be concerned about identifying the motivating and inhibiting factors that impact the usage of m-health apps among younger generations. While several studies have been carried out in Europe (e.g. Nunes et al., 2019) and the US (e.g. Yuan et al., 2015) to address m-health adoption, a research gap still exists in developing countries (Nguyen *et al.*, 2022). Moreover, studies on m-health app use among Gen-Z are limited and findings from existing studies should be carefully generalized to different cultures. Factors such as the health education received by individuals, legislation, and cultural norms regarding the sharing of personal information, may all contribute to conflicting findings. Considering the rapidly changing technological landscape and the expanding mobile app ecosystem, there is a need for further research to identify and provide insights on reducing barriers to widespread access, dissemination, and use of m-health applications.

Research Setting: Healthcare and Gen Z in Turkey

We selected Turkey as the research setting given its position as one of the rapidly growing mobile app markets ranking in the Top 10 worldwide (App Annie, 2019), its success story within the global public health systems[1], and the inherent Eastern and Western aspects of culture. With 65.9% of the population using the Internet to search for health-related information, mobile app usage is high both in the general population and among Gen Z (Turkish Institute of Statistics, 2021). Gen-Z, individuals born between 1995 and 2010 (Mat Zain *et al.*, 2021), was selected as the target population for several reasons:

- Gen-Z is digitally native and embraces mobile technologies more easily making them promising recipients of m-health initiatives (Coughlin *et al.*, 2007).
- Gen-Z members have the opportunity to develop healthy habits at an early age, enabled and reinforced by mobile technologies, paving the way for a healthy lifestyle, with less reliance on healthcare systems.
- Younger generations such as Gen Z have been observed to use various forms of health technology, ranging from online health record access to fitness and health status tracking systems (Rahman et al., 2021; Yousef et al., 2020).

[1] In 2003, the Ministry of Health adopted a Health Transformation Programme that covered the period of 2003-13 and introduced a more streamlined public health system (Ökem and Çakar, 2015). This programme led to the development of a new health information system, the introduction of compulsory social health insurance and performance-related payments, and the restructuring of the health service delivery. As a result, health status indicators improved despite minor increases in expenditures. For instance, life expectancy at birth is 78.3 in Turkey vs OECD average of 80.6. Additionally despite offering universal health care, Turkey's total expenditure on health as a share of GDP is the lowest among OECD countries at 6.3% of GDP (OECD average: 9.3%) (Atun, 2015; OECD, 2022).

- There is a significant lack of studies focusing on Gen-Z in the mobile health application literature.

Against this backdrop, this study contributes to the discussion on electronic health (e-health) and m-health use by providing evidence from Turkey, an emerging economy where 92% of households have access to the Internet (Turkish Institute of Statistics, 2021). Turkey is a prominent mobile device and app market with a ratio of 91.4% active mobile devices per population (Kemp, 2022). The interest in health and fitness applications has increased due to the Covid-19 pandemic, as evidenced by a 76% increase in installations in 2020 (Icozu, 2020).

This study aims to provide valuable insights to policymakers, private institutions, and mobile app developers in increasing the adoption of mobile health apps. To achieve this goal, the study focuses on the following research aims:

RA1. Investigate Gen-Z members' intention to use mobile health apps.

RA2. Identify the determinants of Gen-Z members' intention to use m-health applications.

RA3. Examine the motives that drive Gen-Z members to use mobile health apps.

RA4. Reveal significant factors that facilitate or inhibit the use of mobile health apps among Gen-Z.

Literature review and hypotheses development

Mobile health and mobile applications

The rapid proliferation of smartphones has provided an excellent platform for third-party app developers to enhance the functionality of these devices, paving the way for the expanded use of technology to improve and sustain health. Mobile devices and applications can facilitate changes in user attitudes and behaviour by distributing, collecting, processing and interpreting health-related information using hardware and sensors on devices. The use of such mobile devices and technologies is commonly referred to as ‘mobile health’ (m-health), which the World Health Organization (2011) defined as “medical and public health practice supported by mobile devices, such as mobile phones, patient monitoring devices, personal digital assistants (PDAs), and other wireless devices.”

M-health may be effective in addressing the challenges in public health systems arising from an ageing population, a growing number of patients with chronic diseases, as well as pandemics. Mobile devices and mobile applications can serve as preventive medicine tools by promoting healthy behaviour and lifestyles in numerous ways discussed in the following sections (Bettiga *et al.*, 2020; Helbostad *et al.*, 2017).

Gen-Z and mobile health

Studies on m-health indicate that age is a significant moderator and has an influence on adoption behaviour and its antecedents (Zhao *et al.*, 2018). For instance, Lv, *et al.*’s (2012) study on three age groups revealed that several antecedents have different impacts on behavioural intentions. Similarly, Guo et al. (2016) found that the effects of personalization on trust and behavioural intentions are stronger for younger people compared to older people. The existing literature focusing on Generation Z in the context of m-health is scarce and most similar studies focus on digital interventions and e-health initiatives rather than m-health apps (Aydin and Kumru, 2022; Curtis *et al.*, 2019; Nguyen *et al.*, 2022). However, the characteristics of this generation such as being digitally native, being digitally native and having been born in an era where Internet-enabled mobile devices are easily accessible, make them prospective users of m-health services (Coughlin et al., 2007). Research on Gen Z indicates that they use various e-health initiatives such as personal health records and certain m-health services that track fitness and health status (Rahman et al., 2021; Yousef et al., 2020). Studies also suggest that despite a low adoption of m-health apps among Gen-Z, they are commonly satisfied with the m-health apps they use (Do *et al.*, 2018; Nguyen *et al.*, 2022). Studies focusing on interventions using novel technologies such as the internet and social media have shown that these can be used as feasible and effective digital interventions and younger generations are open to using these initiatives (Curtis *et al.*, 2019; Prout Parks *et al.*, 2018).

Benefits of m-health apps

Various objectives can be achieved through m-health applications that target the general population. Olla and Shimskey (2015) proposed an eight-category taxonomy to classify m-health apps: point-of-care diagnostic, patient monitoring, wellness, education and reference, compliance, behavior modification, efficiency and productivity and patient monitoring. In this study, we focus on m-health applications that can be classified as preventive medicine tools. Among those m-health apps, several subcategories are evident (Aydin and Silahtaroglu, 2021). Self-tracking using mobile apps is related to various outcomes in those subcategories. When individuals track their behaviour, they begin to quantify their habits and themselves (Gimpe *et al.*, 2013).

One of the prominent subcategories is establishing healthy eating habits (Burke *et al.*, 2011; Krebs and Duncan, 2015). Maintaining a balanced diet and limiting calorie intake, and achieving a healthy body mass index (BMI) through weight control/loss are among the expected outcomes of these apps. Studies have shown that adherence to diet regimens is higher for mobile device users (e.g. Burke *et al.*, 2012), and individuals following a specific diet while using a supporting mobile application have lower BMIs than those who did not use a mobile app (Turner-McGrievy *et al.*, 2013). Moreover, there is evidence supporting the effectiveness of digital platforms including mobile apps, in improving nutrition in adults and children (Zarnowiecki *et al.*, 2020).

Another popular category of preventive m-health apps focuses on encouraging physical activity (Krebs and Duncan, 2015; Middelweerd *et al.*, 2014). These apps aim to counter inactivity and sedentary behaviour, which have been linked to increased heart disease (World Health Organization, 2010) and rank fourth among causes of death in adults (Kohl *et al.*, 2012). In a related study, users of such an application performed more frequent physical activity, had higher physical activity intent and reached a lower BMI compared to the control group (Turner-McGrievy *et al.*, 2013). Systematic reviews on the use of various mobile apps that aim to improve diet, promote physical activity and change sedentary lifestyle revealed that the apps have statistically significant effects on targeted outcomes (Coughlin *et al.*, 2016; Helbostad *et al.*, 2017; Schoeppe *et al.*, 2016).

In a separate vein, positive outcomes regarding sexual and mental health were also counted among the areas where mobile apps can provide benefits. For instance, according to a recent study, tracking the mood of individuals via a mobile application reduces symptoms related to depression and anxiety and improves emotional well-being (Bakker and Rickard, 2018). Another area where m-health apps aim to be influential in improving public health is quitting alcohol and substance use, smoking, and similar addictions (Abroms *et al.*, 2012). Considering that substance use has become an issue of significance for public health (Bose *et al.*, 2017), this use case emerges as a focal area of related studies (Curtis *et al.*, 2019).

Despite those benefits, it should be mentioned that mobile application use also has a dark side as mobile apps, in general, are known to lead to addiction issues (Chatterjee *et al.*, 2021; Moqbel *et al.*, 2022). In addition, self-tracking technologies (e.g. step/activity counters, calorie logs etc.) (Feng *et al.*, 2021), and patient empowerment via quantified-self movement have received criticism in recent years (Ajana, 2017). Critics highlight the possible adverse outcomes such as self-medication, delaying physician visits and poor quality health information/advice received via m-health apps (Sharon, 2017). Such criticism can be considered to be valid for a small subset of available m-health apps. Yet, based on the evidence from a wide range of studies (e.g. Hearld *et al.*, 2019; Shapiro and Kamal, 2021; Tavares and Oliveira, 2016), it can be argued that mobile apps' benefits for public health outweigh such concerns and m-health apps can provide tangible value in improving individual health and subsequently decrease the burden on health systems.

New technology acceptance and UTAUT

Despite the wide range of use cases and the expected positive outcomes highlighted in the previous section, several barriers to mass adoption exist. Among these, macro-level barriers such as limited access to mobile technologies, and low technology literacy due to income, age or culture are evident. In addition, more generic barriers relevant for a wider range of individuals, including younger generations, exist as well. The determinants of behavioural intentions and relevant barriers considered in the literature mainly originate from the technology adoption literature. Specifically, studies have highlighted the role of a lack of perceived benefits, the complexity of use, privacy concerns regarding personal health information, health literacy, trust in related institutions, and social influence on behavioural intentions and usage (Kim *et al.*, 2017; Krebs and Duncan, 2015; Mackert *et al.*, 2016; Shareef *et al.*, 2014). Understanding and addressing these determinants is critical to ensure the large-scale adoption of m-health applications.

As evidenced in the extant literature on e-health and m-health, a considerable proportion of studies have benefitted from technology adoption models such as the technology acceptance model (TAM), Unified Theory of Acceptance and Use of Technology (UTAUT) and Innovation Diffusion Theory (IDT) by (Rogers, 2003). To establish a relevant framework for the study, we have chosen the UTAUT, the seminal work of Venkatesh et al. (2003) which has reviewed and combined the then-existing literature and influential models on new information technology adoption such as TAM (Davis, 1989), the Theory of Reasoned Action (TRA), the Theory of Planned Behaviour (TPB) (Ajzen, 1991), and the IDT. UTAUT posits that the behavioural intention to use a new information technology can be determined by four constructs: expected effort, expected performance, social influence, and enabling conditions (Venkatesh *et al.*, 2003).

Hypotheses Development

Effort expectancy and performance expectancy

One major element of UTAUT, the effort expectancy construct, assesses the perception of how easy/complex a novel service is to use, which is similar to the ease of use construct of TAM and IDT. Effort expectancy is defined as ‘‘the degree of ease associated with consumers’ use of technology’’ (Venkatesh *et al.*, 2003). Within this study’s context, when a mobile application is complex, and more effort is needed to effectively use it, users will be less likely to use that app (Dwivedi *et al.*, 2016). Consequently, improving mobile app interfaces, streamlining the steps to use, and decreasing the amount of data input will inherently increase the propensity to use mobile apps. Performance expectancy, on the other hand, is similar to the perceived usefulness construct of TAM and the relative advantage construct of IDT, and is defined as the "degree to which using a technology will provide benefits to users in performing certain activities" (Venkatesh *et al.*, 2003). Thus, performance expectancy manifests the utilitarian value provided to users by new technology (e.g. m-health applications). The utilitarian benefits of m-health apps are linked to the aims of the app, such as monitoring and managing a health situation or adopting (avoiding) healthy (unhealthy) behaviour. The proposed effects of effort expectancy and performance expectancy on behavioural intentions have been confirmed by several researchers in e-health contexts (Cimperman *et al.*, 2016; Jung and Loria, 2010). Moreover, studies on general m-health use (Alaiad *et al.*, 2019; Coughlin *et al.*, 2016; El-Wajeeh *et al.*, 2014; Nunes *et al.*, 2019) and disease management (Zhang *et al.*, 2019), as well as more specific contexts such as m-health apps that promote physical activity (Liu *et al.*, 2019; Wei *et al.*, 2021; Yuan *et al.*, 2015) and mental health (Keen and Roberts, 2017) have confirmed the significant role of effort expectancy and performance expectancy on behavioural intentions. Thus, we hypothesize the following:

H_1: Effort expectancy is positively related to the intention to use m-health apps.

H_2: Performance expectancy is positively related to the intention to use m-health apps.

Social influence

The social influence construct of UTAUT, which was adopted from the TPB, refers to the degree to which an individual perceives that others important to him/her believe that he/she should use the technology. Several studies founded upon UTAUT and TPB have tested for and established that social influence had a significant impact on intentions in telehealth and m-health contexts (Alaiad *et al.*, 2019; Bettiga *et al.*, 2020; Cimperman *et al.*, 2016; Nunes *et al.*, 2019). Considering that mobile apps work on personal mobile devices, which are mainly used to communicate with peers, friends, and family, the significance of social influence may even be more pronounced. Moreover, high mobile device penetration and social media use starting from an early age among Gen-Z may also augment the importance of social influence on behavioural intentions (Business Insider, 2019). A meta-analysis by Williams et al. (2015) on studies founded on UTAUT also confirmed that the majority of the studies, but not all (86 out of 110), demonstrated a significant relationship between SI and behavioural intentions. Thus, despite the evidence provided by studies on m-health services (Alaiad *et al.*, 2019; Alam *et al.*, 2019; del Río-Lanza *et al.*, 2020; Sun *et al.*, 2013) and mobile apps (Bettiga *et al.*, 2020; Keen and Roberts, 2017; Ndayizigamiye *et al.*, 2020; Nunes *et al.*, 2019), not all findings indicate a significant role of social influence on m-health app use. For instance, Yuan et al. (2015) and Huang and Yang (2020) found insignificant effects of social influence on user behaviour and behavioural intentions, respectively. This may partly be attributed to the differences in context and sample characteristics. Additionally, social influence may have a stronger effect on initial use but a weaker effect on continued use and adoption as friends, colleagues and family can influence the trial behaviour but possibly not long-term behaviour. This phenomenon calls for further studies to refute or support the assumed relationship in related settings, consequently, the following is hypothesized:

H_3: Social Influence is positively related to the intention to use m-health apps.

Facilitating conditions

The facilitating conditions construct of UTAUT is similar to the perceived behavioural control concept in the TPB. Facilitating conditions are defined as external factors that can either facilitate or hinder the acceptance of a new technology/service (Venkatesh *et al.*, 2003). Possible facilitating conditions that affect behaviour include relevant knowledge individuals have, relevant training received, the support provided to use new devices/technologies, or the ability to access the new devices/technology in question. In the context of mobile health app use, users need to have access to a mobile device, have the proper knowledge to use the device and the app, and get relevant support from professionals if required. This factor has been shown to influence the intention to use e-health and mobile health services and apps in relevant studies as well (Dwivedi *et al.*, 2016; Kaium *et al.*, 2020; Zhang *et al.*, 2019), thus, we have hypothesized the following:

H_4: Facilitating conditions are positively related to m-health app use.

Privacy risk and trust

In a wide range of m-health apps, users are required to provide personal information such as weight, height, eating, drinking or smoking behaviour, among others, to benefit from the features offered. However, individuals' concern about unauthorized access to their personal health information can lead to a tendency to keep their information private, resulting in a lower inclination to use mobile apps (Lupton, 2014). Privacy in e-health/m-health contexts is a significant concern due to the nature and sensitivity of the information collected (Bansal *et al.*, 2010). A relevant construct, privacy risk, has been used in the literature to address these concerns, which can be defined as the potential loss of control over one's personal information. Accordingly, securing the collected personal information of users via mobile applications emerges as an important topic for mobile app developers and sponsors, with considerations for adhering to legislation, and meeting ethical and personal concerns in the healthcare setting (Krebs and Duncan, 2015; Shareef *et al.*, 2014).

However, effective control mechanisms are commonly unavailable to monitor these relatively new mobile services, making users uncertain about the application providers' intentions and behaviour (Kotz *et al.*, 2009; Martínez-Pérez *et al.*, 2015). For instance, a study on 600 m-health apps highlighted the severity of the topic by revealing that less than one-third of the apps have a privacy policy (Sunyaev *et al.*, 2014). Who can, and in which manner, can access their personal health information is usually unknown to users. Not surprisingly, studies on m-health have demonstrated that privacy concerns and related risks negatively affect users' behavioural intentions (Alqahtani and Orji, 2020; El-Wajeeh *et al.*, 2014; Guo *et al.*, 2016; Wei *et al.*, 2021). Therefore, privacy concerns and related risks emerge as a barrier to m-health adoption, thus, we hypothesize the following:

H_5: Privacy risk is negatively related to the intention to use m-health apps.

Consumer behaviour literature suggests that individuals usually hesitate to share personal information with service providers that they are not familiar with (Chellappa and Sin, 2005). This concept is considered separately from an individual's privacy concerns. This issue which is specific to consumer perceptions of service providers is commonly explored using the "trust" construct and has been examined in various settings such as e-health adoption, due to its proposed role in reducing uncertainty and enhancing desirable behaviour (Chellappa and Sin, 2005; Salo and Karjaluoto, 2007). Trust can be defined as a belief that one party can rely on a word or promise given by another party (Zaltman and Moorman, 1988). Trust in the service provider can be instrumental in overcoming risk-related obstacles such as the risk of obtaining inaccurate information, or technical issues related to security and privacy (Jung and Loria, 2010). Conversely, a lack of trust in a provider may result in consumers' rejection of services and systems provided by unfamiliar vendors as trust is found to be influential in decision-making (Chellappa and Sin, 2005; Guo *et al.*, 2016).

Moreover, trust can eliminate the uncertainty about the potential adverse behaviour of service providers, and thus may be influential in overcoming user concerns (Dinev *et al.*, 2016; Guo *et al.*, 2016). Several studies have confirmed the positive relationship between trust in a service provider and behavioural intentions in m-health settings (Akdur *et al.*, 2020; Akter *et al.*, 2013; Deng *et al.*, 2018; El-Wajeeh *et al.*, 2014; Guo *et al.*, 2016). Additionally, users' privacy concerns regarding the unintended use of personal information can be lessened by establishing trust in related organizations (Dinev *et al.*, 2016). Thus, we hypothesize the following:

H_6: The level of user trust in organizations providing and sponsoring m-health apps is negatively related to privacy risk.

H_7: The level of user trust in organizations providing and sponsoring m-health apps is positively related to the intention to use m-health apps.

Extending UTAUT: e-health literacy and enjoyment

Individuals need digital skills and a certain level of health literacy to effectively use e-health initiatives and digital tools, such as mobile apps, to attain intended outcomes. A lack of these skills may hinder the use and adoption of m-health apps. A construct that can measure such literacy, and which applies to m-health will help understand related consumer behaviour. Thus, we incorporated the e-health literacy construct (eHeals), developed by Norman and Skinner (2006) to assess consumers' perceived skills at using information technology for health, into the research model. To understand and utilize mobile health apps effectively, users need to have a certain level of e-health literacy skills and a lack of such literacy creates a barrier to adoption (Aydin and Kumru, 2022; Wilson *et al.*, 2021). Consequently, users with better e-health literacy are expected to have higher intentions to use mobile apps (Kim *et al.*, 2017):

H_8: E-health literacy level is positively related to the intention to use mobile applications.

In the technology adoption literature, hedonic motivation, which refers to the pleasure derived from using a technology product, has been incorporated into models such as TAM and UTAUT through enjoyment and playfulness constructs to improve their ability to predict behaviour (Moon and Kim, 2001; Ryan and Deci, 2000; Venkatesh and Bala, 2008). Despite the fact that health apps are not primarily designed to offer enjoyment, incorporating enjoyable features can help promote the apps and keep users engaged (Abroms *et al.*, 2012; Yuan *et al.*, 2015). Relatedly, several studies on mobile apps have also explored the role of hedonic motivation on behavioural intentions by incorporating constructs such as enjoyment (Dwivedi *et al.*, 2016; Katheeri, 2020; Tavares and Oliveira, 2016; Yuan *et al.*, 2015) or entertainment gratification (Lee and Cho, 2017) into their models. However, some studies in the e-health and m-health contexts have yielded inconsistent findings regarding the hypothesized relationship (e.g. Huang and Yang, 2020). Consequently, we aim to examine this proposed effect by testing the following hypothesis:

H_9: Enjoyment is positively related to the intention to use m-health apps.

Focal constructs: behavioural intentions and use behaviour

Use behaviour (i.e. usage) and behavioural intentions are the two major constructs that have been treated as focal constructs to describe technology adoption. Behavioural intentions, defined as ‘a measure of the strength of one's intention to perform a specified behaviour’ (Davis, 1989) was incorporated into UTAUT from TRA. In UTAUT, use behaviour was not explicitly defined as the use data was available via system records (Venkatesh *et al.*, 2003). For this study, we adopted a one-item construct from the existing literature on mobile app use. In UTAUT, TPB (Ajzen, 1991) and related literature, behavioural intentions are considered direct predecessors of actual behaviour and several studies in various e-health settings have confirmed the significance of this relationship (Dwivedi *et al.*, 2016; Kijsanayotin *et al.*, 2009; Tavares and Oliveira, 2016; Wei *et al.*, 2021). Therefore, we propose the following hypothesis:

H_{10}: Behavioural intentions are positively related to m-health app use behaviour.

Research Model

Based on the UTAUT theory and the hypotheses developed in this study, we propose the research model displayed in Figure 1.

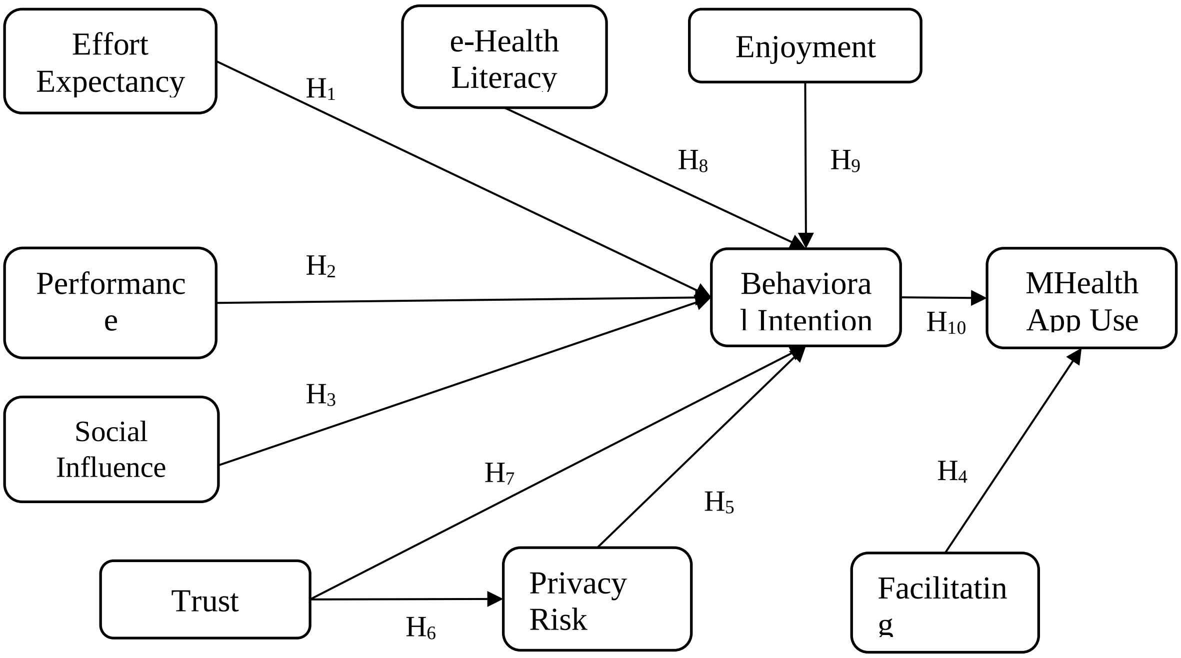


Figure 1. Research Model Source: Authors' own work

Methodology

Sampling

Against this backdrop, university students were selected as the sampling frame to reflect the views of Gen-Z. Considering students' relatively high mobile technology literacy and mobile application usage, a student sample was deemed suitable for reaching respondents with mobile health app usage experience. Given Turkey's high urbanization rate of 93% (Turkish Statistics Institute, 2021), Istanbul with its 18 million population and diverse cultural make-up of Turkey was chosen to conduct the survey study. Istanbul attracts students throughout the country and is home to 56 universities, of which three were selected to carry out the study. Using purposive sampling, 630 eligible students (i.e. aged 18-24, have owned a smartphone and have experience with mobile health apps) were contacted face to face during lectures.

Measures

Information on mobile application usage, behavioral intentions and its antecedents were collected through a survey study. A questionnaire, was developed by adapting and using existing scales from prior research. The questions provided in Table IV in the Appendix were translated from English to Turkish by a bilingual staff member and then translated back to English by a different professor. Also, a pre-test on 5 academic personnel and 10 University students was carried out before finalizing the survey to improve the wording and general layout.

Data collection

Participants in the survey study were informed about the objective and the scope of the study at the beginning of the survey. It was indicated that participation is voluntary, and no contact info is being collected. No incentive was provided for participation in the survey study. First, two filter questions were used to screen out the respondents without smartphones or any m-health app experience. Second, questions regarding mobile app use, determinants of intentions, and attitudes were asked. Finally, demographic questions were asked, and the survey was finalized. The data was coded and verified in SPSS 21 for low-quality answers (e.g. all coded the same way) before moving on to structural equation modelling analysis. Considering the high number of relationships to be tested that increase the complexity of the structural model, partial least squares structural equation modelling (PLS-SEM) was preferred as the analysis method (Hair *et al.*, 2011; Ringle *et al.*, 2012). PLS-SEM is a robust method for analysing complex composite models in exploratory research and its popularity is increasing in various healthcare service settings (Avkiran, 2018). The obtained sample size was tested for adequacy to carry out PLS-SEM analysis using the inverse square root method proposed by Kock and Hadaya (2018). A sample size of 275 was required to detect path coefficients that were equal to or greater than 0.15 according to the calculations. Consequently, we accepted the obtained sample size as adequate for carrying out PLS-SEM analysis. Using Smart PLS 3.2 software, we ran 5,000 bootstrap samples to arrive at the significance levels of paths.

Table I. Sample profile Source: Authors' own work

Characteristic	**Value**	**Frequency**	**Percent**
Mobile App Download Frequency per Month	None	26	8.3%
	1-2	201	64.4%
	3-5	54	17.3%
	6-10	18	5.8%
	11+	13	4.2%
Smart Phone Use Experience (years)	Less than 1 year	1	0.3%
	1-3 years	15	4.8%
	3-5 years	62	19.9%
	5-8 years	157	50.3%
	8+ years	78	24.7%
Age Group	18	17	5.4%
	19	43	13.8%
	20	92	29.5%
	21	77	24.7%
	22	34	10.9%
	23	10	3.2%
	24	39	12.5%
Gender	Female	194	62.2%
	Male	118	37.8%
Household Income	0-350 USD	16	5.1%
	351-700 USD	77	24.7%
	701-1,050 USD	86	27.6%
	1,051-1,400 USD	59	18.9%
	1,401-1,750 USD	21	6.7%
	1,751 USD+	53	17.0%
Self-rated Health Status	Poor	10	3.2%
	Fair	38	12.2%
	Good	129	41.3%
	Very Good	102	32.7%
	Excellent	33	10.6%
Work Status	Student only	245	78.5%
	Working full-time	30	9.6%
	Working part-time	37	11.9%
Total		**312**	**100%**

Analysis Results

Respondent data

360 students participated in the self-administered survey study (57% response rate). A total of 48 questionnaires were left out of further analysis due to missing responses or

poor quality. The final sample profile is provided in Table I.

Validity, reliability and common method variance

The validity and reliability measures were evaluated using the recommended criteria, the results of which are provided in Table II. Internal consistency was assessed using composite reliability (CR), Cronbach's alpha (CA), and Dijkstra's Rho_A, which all exceeded the 0.7 threshold (Henseler *et al.*, 2016). Subsequently, the convergent validity of the model was evaluated through the average variance extracted (AVE) and outer loadings of the constructs. All outer loadings that are provided in Table V in the Appendix were greater than 0.70, and the values of AVE were greater than 0.50. These indicated that the items explained the required variation levels in each latent variable, and the convergent validity conditions were met (Hair *et al.*, 2017).

Table II. Validity and reliability analysis Source: Authors' own work

	# of items	Mean	S.D.	C.A.	rho_A	C.R.	AVE	ELIT	EFEX	ENJO	FACC	USEB	PERF	PRIV	SOCI	TRUS	INTE
ELIT	8	3.72	0.989	0.936	0.941	0.947	0.691	0.831	0.365	0.398	0.527	0.189	0.322	0.121	0.189	0.211	0.192
EFEX	4	3.45	0.945	0.838	0.858	0.892	0.677	0.324	0.823	0.379	0.626	0.192	0.505	0.467	0.318	0.546	0.539
ENJO	3	3.24	1.030	0.920	0.924	0.950	0.863	0.372	0.333	0.929	0.375	0.405	0.751	0.295	0.431	0.473	0.697
FACC	3	3.70	1.006	0.817	0.842	0.880	0.651	0.483	0.461	0.303	0.876	0.284	0.481	0.394	0.240	0.421	0.393
USEB	1	1.41	0.492	1.000	1.000	1.000	1.000	0.185	0.176	0.389	0.260	1.000	0.292	0.055	0.301	0.235	0.382
PERF	4	3.50	1.001	0.938	0.939	0.956	0.843	0.304	0.452	0.697	0.359	0.321	0.918	0.469	0.401	0.623	0.694
PRIV	4	2.89	1.076	0.902	0.922	0.931	0.771	-0.112	-0.419	-0.275	-0.274	-0.124	-0.439	0.878	0.203	0.629	0.471
SOCI	4	2.87	1.010	0.866	0.869	0.909	0.715	0.177	0.284	0.391	0.163	0.295	0.372	-0.193	0.845	0.504	0.624
TRUS	5	3.19	1.004	0.882	0.890	0.914	0.680	0.192	0.469	0.426	0.282	0.243	0.573	-0.583	0.446	0.825	0.613
INTE	4	3.06	1.112	0.918	0.920	0.943	0.805	0.183	0.477	0.641	0.282	0.339	0.645	-0.439	0.564	0.556	0.897

Notes: Square-roots of AVE are provided on the diagonal, correlations below the diagonal and HTMT over the diagonal. ELIT: eHealth Literacy; EFEX: effort expectancy; ENJO: enjoyment; FACC: facilitating conditions; PRIV: privacy concerns; SOCI: social influence; TRUS: trust; INTE: use intentions; PERF: performance expectancy, USEB: Use behaviour (adoption)

The discriminant validity was evaluated using three distinct methodologies. First, the loadings of the indicators that are presented in the Appendix (Table V) were assessed, which loaded more highly on their own construct than on any other construct. As a second measure, the square roots of AVE, provided on the diagonal of Table II, were compared with the correlations between variables, which were all lower than the square-roots of AVE (Fornell and Larcker, 1981; Hair *et al.*, 2017). Finally, the heterotrait-monotrait (HTMT) ratios of correlations were calculated to be lower than the 0.90 threshold (Henseler *et al.*, 2015). Consequently, we concluded that the discriminant validity conditions were satisfied. Furthermore, the variance inflation factor values, which were all lower than 5 further indicated the lack of multicollinearity in the research model.

To address the concern for common method variance, we took several measures starting from the design and administration of the study. Firstly, we assured the anonymity of survey respondents and made clear that there are no right or wrong answers. In the questionnaire, no double-barrelled questions were asked, technical terms were avoided when possible, and questions were kept concise to avoid confusion. Following the coding of data, the severity of the common method variance was tested using Harman's single-factor test. Harman's single-factor test result value of 32.4% denotes that the variance explained by the one-factor solution is lower than the 50% threshold. Furthermore, we tested for common method variance using full collinearity VIFs and the calculated values ranging between 1.42 and 2.75 indicate that common method variance is not a significant issue in the present study.

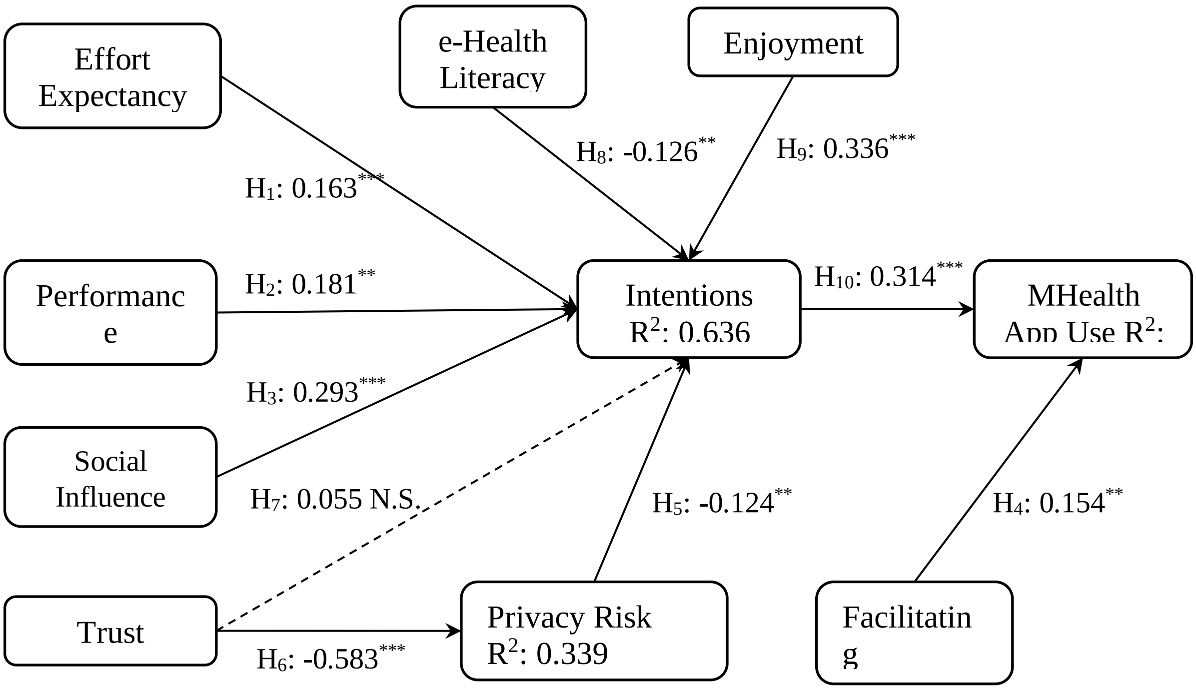
Goodness of fit and predictive relevance

Given that there is no single generally accepted criterion for measuring the goodness-of-fit in PLS-SEM models, several indicators were evaluated in this study, including the coefficient of determination (R^2) for latent variables, the statistical significance levels of the paths, Stone-Geisser's Q^2 value, standardized root mean square residual (SRMR) and root mean square residual covariance (RMS_{theta}).

The R^2 value for intentions was calculated as 0.636, and actual behaviour as 0.160 indicating that the model accounted for substantial amounts of variance and has good predictive power (Hair *et al.*, 2017). The SRMR value of 0.061 and RMS_{theta} value of 0.12 implied an acceptable fit (Henseler *et al.*, 2016). Finally, Stone-Geisser's Q^2 value (Geisser, 1974; Stone, 1974) was calculated using a sample reuse technique, the blind-folding procedure, that omits every n^{th} data point. By choosing an omission distance of seven, the Q^2 value for intentions was calculated as 0.504, and for use behaviour as 0.086, indicating good predictive relevance for the model (Hair *et al.*, 2017). Based on these findings, we conclude that the model fits the data properly and has good predictive power.

Path analysis results

According to the direct effects (paths) provided in Table III and Figure 2, all hypotheses except H_7 were accepted.



*Significance levels: * <0.05; **<0.01; ***<0.001*

Figure 2. Path Analysis Results Source: Authors' own work

The largest effect observed in the study was the offsetting effect of trust on privacy risk. In addition to assessing the significance of paths, effect sizes were also calculated to determine the intensity of the effects indicated by the path coefficients. Values below 0.02 are considered non-significant, 0.02-0.15 weak, 0.15-0.35 medium, and greater than 0.35 large (Cohen, 1992). The results showed that the largest effect on intentions originated from social influence, which was of medium magnitude, followed by enjoyment. Conversely, no significant effect of trust on intentions was detected in the analysis. The influence of performance expectancy, effort expectancy, and privacy risk constructs on intentions were all significant yet weak. Subsequently, the study found that both behavioural intentions and facilitating conditions had positive effects on m-health app use. The "Discussions" section elaborates thoroughly on all the results and provides theoretical and practical implications.

Table III. Direct effects and hypotheses testing results Source: Authors' own work

Path(s)	Mean	St.Dev.	T-stat	Decision	Effect size f^2
H1: Effort Expectancy -> Intentions	0.163	0.048	3.438^{***}	**Supported**	0.049
H2: Performance Expectancy -> Intentions	0.181	0.063	2.856^{**}	**Supported**	0.036
H3: Social Influence -> Intentions	0.293	0.055	5.309^{***}	**Supported**	0.174
H4: Facilitation Conditions -> MHealth App Use	0.154	0.050	2.981^{**}	**Supported**	0.025
H5: Privacy Concerns -> Intentions	-0.124	0.050	2.460^{*}	**Supported**	0.026
H6: Trust -> Privacy Risk	-0.583	0.042	13.812^{***}	**Supported**	0.514
H7: Trust -> Intentions	0.054	0.062	0.891	Not Supported	0.004
H8: E-Health Literacy -> Intentions	-0.126	0.047	2.691^{**}	**Supported**	0.036
H9: Enjoyment -> Intentions	0.336	0.052	6.447^{***}	**Supported**	0.145
H10: Intentions -> MHealth App Use	0.314	0.054	5.767^{***}	**Supported**	0.103

*Significance levels: * <0.05; **<0.01; ***<0.001*

Discussion

The findings of the present study are discussed under theoretical and practical implications sub-sections to offer an easier read to readers with different interest areas and priorities.

Theoretical implications

The results indicate that the effort expectancy and performance expectancy constructs were positively related to behavioural intentions. These well-established relationships have been exhibited to be relevant in m-health contexts previously, and performance expectancy has a stronger influence than effort expectancy, consistent with the majority of the findings in the literature. (Alaiad *et al.*, 2019; del Río-Lanza *et al.*, 2020; Wei *et al.*, 2021; Yuan *et al.*, 2015). This finding aligns with the majority of the existing literature, demonstrating that an individual's willingness to use m-health apps is influenced by peers, friends, and trusted others. Differing from similar studies' findings (e.g. Alam *et al.*, 2019; Sun *et al.*, 2013), the size of this effect is larger than performance expectancy. This finding highlights the crucial role that peers and social groups play in shaping the behavioural intentions of Gen-Z members.

Our results confirmed that UTAUT is valid in the m-health app context in developing countries and established that effort expectancy is a significant factor influencing the adoption behavior of Gen-Z, who are considered to have high digital literacy. However, the findings also signified that UTAUT's refinement is crucial to capture the distinct aspects of m-health use. It is evident that the inclusion of the enjoyment construct, which highlights the marketing aspect of mobile apps, in addition to the privacy risk and e-health literacy constructs, enriches the understanding offered by UTAUT. This outcome is a relevant theoretical contribution, extending UTAUT and setting the stage for future research about the role of hedonic motivation on mobile health app use and acceptance. Entertaining features and content are used commonly in marketing communications and digital and mobile services, yet they are not at the forefront within the m-health setting. The young population in developing countries can be targeted using such entertaining features.

Our results also highlight that privacy risk is negatively related to behavioural intentions. This finding confirms the literature (Alam *et al.*, 2020; Alqahtani and Orji, 2020; Guo *et al.*, 2016; Leong *et al.*, 2020) and signifies that respondents are concerned about unauthorized access to and unintended use of their health information. On the other hand, the findings fail to exhibit a direct relationship between the level of trust in the sponsor/developer of the mobile app and behavioural intentions of respondents. This is an interesting finding the cause of which may be partly attributable to the nature of app marketplaces in which thousands of apps compete for the attention of the users. Most apps are developed by smaller companies whom the target audience may not be aware of (IBISWorld, 2023). Thus, trust establishment may be harder, especially for younger people in developing countries where exposure to global companies and the English language is limited, and instead, the potential users may be drawn towards user reviews rather than assessing the trustworthiness of app developers (Burgers *et al.*, 2016).

Moreover, e-health literacy was found to have a weak but negative influence on intentions. This finding contrasts our initial proposition of a positive effect. One plausible reason is the readily available health information provided on alternative channels such as websites (Aydin, 2020; Lin *et al.*, 2016), which may decrease the benefits offered by m-health apps and may make them redundant for certain individuals. Thus, depending on the use case, individuals with high e-health literacy may seek, access and use available information on the Internet without any particular need for m-health apps. Furthermore, users with high e-health literacy are expected to have a better health status, thus, may not feel the need to use m-health apps and have a low intention to use them. Gen-Z members' knowledge thus e-health literacy may differ between countries as the curriculum in each country differs from each other, thus further comparative studies may shed light on this phenomenon.

As another theoretical implication, behavioural intentions were found to be direct predecessors of m-health use. This inherent relationship confirms similar postulations of consumer behaviour models, such as TPB and UTAUT, in an m-health app setting. Moreover, we detected the weakest relationship in the model in terms of the effect size between facilitating conditions and m-health app use. This may mainly be attributed to the young and educated sample (i.e. Gen-Z member university students) who have the means and digital literacy to use mobile apps. This finding confirms the majority of the relevant technology adoption literature where a weak effect was observed (Alam *et al.*, 2020; Ndayizigamiye *et al.*, 2020; Yuan *et al.*, 2015).

When we consider the theoretical implications related to Gen Z, there are three important implications to highlight. Firstly, it is evident that Gen-Z members demand easy-to-use apps that offer utility, but there exist more influential factors affecting their usage of m-health apps. Specifically, social influence (i.e. subjective norms) has a stronger impact on the intention to use m-health apps among Gen-Z members. Secondly, enjoyment emerges as a significant factor that influences the usage intentions of Gen-Z. It can be argued that this younger generation expects and values enjoyable experiences across a wide range of services, including m-health, as also noted by Nguyen et al. (2022). Lastly, similar to other generational cohorts, Gen-Z members are concerned about the privacy of their personal health information which is a noteworthy barrier to their adoption of m-health apps.

Practical implications

Building upon the theoretical implications discussed earlier, social influence can play a key role in increasing the adoption of mobile health apps. Features that allow users to share progress with family and friends, and social media integrations can help tap into this phenomenon. Additionally, integrating entertaining features that offer enjoyment to users, such as points, badges, leaderboards, display of progress, virtual rewards, social media integration, and user-to-user interactions can increase adoption among younger generations.

As another practical implication, facilitating conditions and effort expectancy are less likely to emerge as considerable barriers to m-health usage among educated and young generations as compared to other factors analysed. Consequently, efforts may be better directed elsewhere, such as improving the entertaining features of apps to provide a more enjoyable experience. Practitioners are encouraged to consider to prioritize user experience (UX) design to offer enjoyable experiences when using apps. Evoking higher levels of enjoyment among users will facilitate the adoption of mobile health apps among younger generations, which can subsequently be influential in improving public health. Displaying progress, setting goals, earning badges and intangible/virtual rewards can be counted among app features that can provide enjoyment.

The study found a strong offsetting influence of trust on privacy risk, indicating that building trust among young individuals, specifically Gen-Z members, towards mobile app developers and sponsors such as healthcare providers, can decrease privacy risks and indirectly lead to wider usage of m-health apps. Given that privacy concerns and related risks are counted among significant barriers to e-health and m-health adoption (Angst and Agarwal, 2009; Krebs and Duncan, 2015), promoting trust becomes a viable way to address such concerns. In addition, privacy concerns should be tackled through improved transparency and user control over the information stored in m-health apps and presenting data in a manner that respects users' privacy can help in the wider adoption of m-health services (Klasnja and Pratt, 2012).

Furthermore, positive and encouraging external influence from peers can lead to the adoption of mobile health apps that promote healthy living and act as preventive medicine tools, even among young and healthy individuals. Therefore, as a practical implication, m-health app developers and sponsors should not overlook the importance of improving the social desirability of apps. Offering social media integration and user-to-user interactions in apps emerge as more prominent measures than merely improving the ease of use of m-health applications when targeting Gen-Z.

Limitations and further research directions

Despite its contributions to the literature, this study has several limitations. First, a non-random sampling method, purposive sampling was used, and the sample consisted of students. Hence, one future research avenue emerges as reaching a larger sample that can represent the related generational cohort in Turkey in a better way. In addition to offering possibly better representativeness, a large sample from a multitude of countries/cultures may also facilitate multi-group analyses, which can offer insights into the differing ways intentions are influenced among different user segments. Second, this study focused on specific antecedents of intentions regarding mobile app use and extended a popular technology acceptance model, UTAUT. Conducting further studies on similar theoretical foundations can help arrive at more reliable and generalizable results through triangulation. Moreover, we have adopted a unidimensional trust construct yet given its strong influence on privacy risk, the important role that trust may play in m-health adoption can be pondered in more detail with a multi-faceted trust construct. Given the enjoyment's observed strong impact on behavioral intentions, further research can also investigate the relationship between enjoyment and behavioral intentions in more detail to understand its more effective use in the mobile health app context. Lastly, incorporating several instances of actual mobile app use data in longitudinal studies can provide further insights into m-health app adoption and changes in behaviour over time.

Conclusion

Mobile health apps can help establish and sustain healthy habits for years making Gen-Z, the youngest generational cohort, a viable target for the widespread adoption of m-health apps. Within this setting, the present study on Gen-Z contributes to the current knowledge on m-health, a novel and popular research topic of concern to policymakers, technology developers and healthcare managers in several ways. Firstly, the study's context differs from the common, developed Western cultural setting and focuses on a developing country, Turkey, situated at the crossroads of Europe and Asia. Turkey, with a relatively young population, provides insights into developing markets and mixed cultures, yet no directly comparable studies have been carried out in this setting.

Additionally, our results indicate that UTAUT can be applied to mobile health app adoption successfully. However, our findings also indicate that other constructs are called for to improve the model's explanatory power and to further our understanding of the underlying consumer behaviour. For instance, our findings highlight the importance of hedonic motivation, which is often overlooked in health settings, but has a more significant effect than both the utility provided by the apps and the effort needed to use the apps. Therefore, promoting features that can provide enjoyment in apps (e.g. through gamification mechanics and good UX design) is crucial in attracting the younger population. Moreover, privacy concerns, which are of utmost significance in both health and mobile settings, and a relevant literacy construct (i.e. e-health literacy) add value to the UTAUT model and help explain changing consumer behaviour in the digitization of health services. The present study contributes to a research gap by addressing the role of trust in overcoming privacy concerns, as only a handful of studies on m-health adoption have considered this relationship.

REFERENCES

Abroms, L.C., Padmanabhan, N. and Evans, W.D. (2012), "Mobile phones for health communication to promote behavior change", in Noar, S. and Harrington, N. (Eds.), *EHealth Applications: Promising Strategies for Behavior Change*, pp. 147–166.

Ajana, B. (2017), “Digital health and the biopolitics of the Quantified Self”, *DIGITAL HEALTH*, Vol. 3, p. 205520761668950.

Ajzen, I. (1991), “The theory of planned behavior”, *Organizational Behavior and Human Decision Processes*, Vol. 50, pp. 179–211.

Akdur, G., Aydin, M.N. and Akdur, G. (2020), “Adoption of Mobile Health Apps in Dietetic Practice: Case Study of Diyetkolik”, *JMIR MHealth and UHealth*, Vol. 8 No. 10, p. e16911.

Akter, S., Ray, P. and D’Ambra, J. (2013), “Continuance of mHealth services at the bottom of the pyramid: The roles of service quality and trust”, *Electronic Markets*, Vol. 23 No. 1, pp. 29–47.

Alaiad, A., Alsharo, M. and Alnsour, Y. (2019), “The Determinants of M-Health Adoption in Developing Countries: An Empirical Investigation”, *Applied Clinical Informatics*, Vol. 10 No. 05, pp. 820–840.

Alam, M.Z., Hu, W., Hoque, M.R. and Kaium, M.A. (2019), “Adoption intention and usage behavior of mHealth services in Bangladesh and China”, *International Journal of Pharmaceutical and Healthcare Marketing*, Vol. 14 No. 1, pp. 37–60.

Alam, M.Z., Hu, W., Kaium, M.A., Hoque, M.R. and Alam, M.M.D. (2020), “Understanding the determinants of mHealth apps adoption in Bangladesh: A SEM-Neural network approach”, *Technology in Society*, Vol. 61, p. 101255.

Alqahtani, F. and Orji, R. (2020), “Insights from user reviews to improve mental health apps”, *Health Informatics Journal*, available at:https://doi.org/10.1177/1460458219896492.

Angst, C.M. and Agarwal, R. (2009), “Adoption of Electronic Health Records in the Presence of Privacy Concerns: The Elaboration Likelihood Model and Individual Persuasion”, *MIS Quarterly*, Vol. 33 No. 2, p. 339.

App Annie. (2019), “The State of the Turkish App Economy”, available at: https://go.appannie.com/State-of-Turkey-App-Economy.html (accessed 20 January 2020).

Atun, R. (2015), “Transforming Turkey’s Health System — Lessons for Universal Coverage”, *New England Journal of Medicine*, Vol. 373 No. 14, pp. 1285–1289.

Avkiran, N.K. (2018), “An in-depth discussion and illustration of partial least squares structural equation modeling in health care”, *Health Care Management Science*, Vol. 21 No. 3, pp. 401–408.

Aydin, G. (2020), “Improving Health and Efficiency With Strategic Social Media Use in Health Organizations”, *Multidimensional Perspectives and Global Analysis of Universal Health Coverage*, IGI Global, pp. 309–336.

Aydin, G. and Kumru, S. (2022), “Paving the way for increased e-health record use: elaborating intentions of Gen-Z”, *Health Systems*, Taylor & Francis, Vol. 00 No. 00, pp. 1–18.

Aydin, G. and Silahtaroglu, G. (2021), “Insights into mobile health application market via a content analysis of marketplace data with machine learning”, *PLoS ONE*, Public Library of Science, Vol. 16 No. 1 January, available at:https://doi.org/10.1371/journal.pone.0244302.

Bakker, D. and Rickard, N. (2018), “Engagement in mobile phone app for self-monitoring of emotional wellbeing predicts changes in mental health: MoodPrism”, *Journal of Affective Disorders*, Vol. 227, pp. 432–442.

Bansal, G., Zahedi, F.M. and Gefen, D. (2010), “The impact of personal dispositions on information sensitivity, privacy concern and trust in disclosing health information online”, *Decision Support Systems*, Elsevier B.V., Vol. 49 No. 2, pp. 138–150.

Bettiga, D., Lamberti, L. and Lettieri, E. (2020), “Individuals’ adoption of smart technologies for preventive health care: a structural equation modeling approach”, *Health Care Management Science*, Health Care Management Science, No. 23, pp. 203–214.

Bose, J., Hedden, S.L., Lipari, R.N. and Park-Lee, E. (2017), “Key Substance Use and Mental Health Indicators in the United States: Results from the 2017 National Survey on Drug Use and Health”, *HHS Publication*, available at: https://www.samhsa.gov/data/sites/default/files/cbhsq-reports/NSDUHFFR2017/NSDUHFFR2017.htm.

Burgers, C., Eden, A., de Jong, R. and Buningh, S. (2016), “Rousing reviews and instigative images: The impact of online reviews and visual design characteristics on app downloads”, *Mobile Media and Communication*, Vol. 4 No. 3, pp. 327–346.

Burke, L.E., Conroy, M.B., Sereika, S.M., Elci, O.U., Styn, M.A., Acharya, S.D., Sevick, M.A., *et al.* (2011), “The effect of electronic self-monitoring on weight loss and dietary intake: A randomized behavioral weight loss trial”, *Obesity*, Vol. 19 No. 2, pp. 338–344.

Burke, L.E., Styn, M.A., Sereika, S.M., Conroy, M.B., Ye, L., Glanz, K., Sevick, M.A., *et al.* (2012), “Using mHealth technology to enhance self-monitoring for weight loss: A randomized trial”, *American Journal of Preventive Medicine*, Vol. 43 No. 1, pp. 20–26.

Business Insider. (2019), “The State of Gen-Z: The smartphone generation is reaching a breaking point.”, available at: https://www.businessinsider.com/gen-z-is-smartphone-generation-2019-7?r=US&IR=T (accessed 10 June 2020).

Ceci, L. (2022), “Number of health and fitness app users in the United States from 2018 to 2022”, *Statista*, available at: https://www.statista.com/statistics/1154994/number-us-fitness-health-app-users.

Chatterjee, S., Chaudhuri, R., Vrontis, D. and Thrassou, A. (2021), “Dark side of smartphone applications and its consequence to the Asian society”, *Journal of Asia Business Studies*, Vol. 16 No. 6, pp. 1006–1029.

Chellappa, R.K. and Sin, R.G. (2005), “Personalization versus privacy: An empirical examination of the online consumer’s dilemma”, *Information Technology and Management*, Vol. 6 No. 2–3, pp. 181–202.

Cimperman, M., Makovec Brenčič, M. and Trkman, P. (2016), “Analyzing older users’ home telehealth services acceptance behavior—applying an Extended UTAUT model”, *International Journal of Medical Informatics*, Vol. 90, pp. 22–31.

Cohen, J. (1992), “A power primer.”, *Psychological Bulletin*, Vol. 112 No. 1, pp. 155–159.

Coughlin, J.F., D'Ambrosio, L.A., Reimer, B. and Pratt, M.R. (2007), "Older adult perceptions of smart home technologies: Implications for research, policy & market innovations in healthcare", *Annual International Conference of the IEEE Engineering in Medicine and Biology - Proceedings*, pp. 1810–1815.

Coughlin, S.S., Whitehead, M., Sheats, J.Q., Mastromonico, J., Smith, S., Mastrominico, J. and Smith, S. (2016), "A Review of Smartphone Applications for Promoting Physical Activity.", *Jacobs Journal of Community Medicine*, Vol. 2 No. 1, pp. 1–14.

Curtis, B.L., Ashford, R.D., Magnuson, K.I. and Ryan-Pettes, S.R. (2019), "Comparison of Smartphone Ownership, Social Media Use, and Willingness to Use Digital Interventions Between Generation Z and Millennials in the Treatment of Substance Use: Cross-Sectional Questionnaire Study", *Journal of Medical Internet Research*, Vol. 21 No. 4, p. e13050.

Davis, F.D. (1989), "Perceived usefulness, perceived ease of use, and user acceptance of information technology", *MIS Quarterly*, Vol. 13 No. 3, pp. 319–340.

Deng, Z., Hong, Z., Ren, C., Zhang, W. and Xiang, F. (2018), "What predicts patients' adoption intention toward mhealth services in China: Empirical study", *JMIR MHealth and UHealth*, Vol. 6 No. 8, pp. 1–14.

Dinev, T., Albano, V., Xu, H., D'Atri, A. and Hart, P. (2016), "Individuals' Attitudes Towards Electronic Health Records: A Privacy Calculus Perspective", *Advances in Healthcare Informatics and Analytics*, Vol. 19, pp. 19–50.

Do, T.T.T., Le, M.D., Van Nguyen, T., Tran, B.X., Le, H.T., Nguyen, H.D., Nguyen, L.H., *et al.* (2018), "Receptiveness and preferences of health-related smartphone applications among Vietnamese youth and young adults", *BMC Public Health*, Vol. 18 No. 1, p. 764.

Dwivedi, Y.K., Shareef, M.A., Simintiras, A.C., Lal, B. and Weerakkody, V. (2016), "A generalised adoption model for services: A cross-country comparison of mobile health (m-health)", *Government Information Quarterly*, Vol. 33 No. 1, pp. 174–187.

El-Wajeeh, M., Galal-Edeen, G.H. and Mokhtar, H. (2014), "Technology Acceptance Model for Mobile Health Systems", *IOSR Journal of Mobile Computing & Application*, Vol. 1 No. 1, pp. 21–33.

Feng, S., Mäntymäki, M., Dhir, A. and Salmela, H. (2021), "How Self-tracking and the Quantified Self Promote Health and Well-being: Systematic Review", *Journal of Medical Internet Research*, Vol. 23 No. 9, p. e25171.

Fornell, C. and Larcker, D.F. (1981), "Evaluating Structural Equation Models with Unobservable Variables and Measurement Error.", *Journal of Marketing Research*, American Marketing Association, Vol. 18 No. 1, pp. 39–50.

Gannon, B., Davis, R., Kuhns, L.M., Rodriguez, R.G., Garofalo, R. and Schnall, R. (2020), "A mobile sexual health app on empowerment, education, and prevention for young adult men (MyPEEPS Mobile): Acceptability and usability evaluation", *JMIR Formative Research*, Vol. 4 No. 4, available at:https://doi.org/10.2196/17901.

Geisser, S. (1974), "A predictive approach to the random effect model", *Biometrika*, Vol. 61, pp. 101–107.

Gimpe, H., Nißen, M. and Görlitz, R.A. (2013), "Quantifying the quantified self: A study on the motivation of patients to track their own health", *International Conference on Information Systems (ICIS 2013): Reshaping Society Through Information Systems Design*, Vol. 4, pp. 3286–3301.

Guo, X., Zhang, X. and Sun, Y. (2016), "The privacy-personalization paradox in mHealth services acceptance of different age groups", *Electronic Commerce Research and Applications*, Elsevier B.V., Vol. 16, pp. 55–65.

Hair, J.F., Hult, G.T.M., Ringle, C.M. and Sarstedt, M. (2017), *A Primer on Partial Least Squares Structural Equation Modeling (PLS-SEM)*, 2nd ed., Sage Publications, Inc, Los Angeles.

Hair, J.F., Ringle, C.M. and Sarstedt, M. (2011), "PLS-SEM: Indeed a Silver Bullet", *The Journal of Marketing Theory and Practice*, Vol. 19 No. 2, pp. 139–152.

Hearld, K.R., Hearld, L.R., Budhwani, H., McCaughey, D., Celaya, L.Y. and Hall, A.G. (2019), "The future state of patient engagement? Personal health information use, attitudes towards health, and health behavior", *Health Services Management Research*, Vol. 32 No. 4, pp. 199–208.

Helbostad, J., Vereijken, B., Becker, C., Todd, C., Taraldsen, K., Pijnappels, M., Aminian, K., *et al.* (2017), "Mobile Health Applications to Promote Active and Healthy Ageing", *Sensors*, Vol. 17 No. 3, p. 622.

Henseler, J., Hubona, G. and Ray, P.A. (2016), "Using PLS path modeling in new technology research: updated guidelines", *Industrial Management & Data Systems*, Emerald Group Publishing Ltd., Vol. 116 No. 1, pp. 2–20.

Henseler, J., Ringle, C.M. and Sarstedt, M. (2015), "A new criterion for assessing discriminant validity in variance-based structural equation modeling", *Journal of the Academy of Marketing Science*, Vol. 43 No. 1, pp. 115–135.

Huang, C.-Y. and Yang, M.-C. (2020), "Empirical Investigation of Factors Influencing Consumer Intention to Use an Artificial Intelligence-Powered Mobile Application for Weight Loss and Health Management", *Telemedicine and E-Health*, Vol. 26 No. 10, pp. 1240–1251.

IBISWorld. (2023), "Smartphone App Developers in the US - Employment Statistics", *Industry Statistics*, available at: https://www.ibisworld.com/industry-statistics/employment/smartphone-app-developers-united-states/.

Icozu, T. (2020), "2020'de mobil sağlık ve fitness uygulaması kullanımı dünya genelinde yükseldi", *Webrazzi*, 20 August.

Jung, M.L. and Loria, K. (2010), "Acceptance of Swedish e-health services", *Journal of Multidisciplinary Healthcare*, pp. 55–63.

Kaium, M.A., Bao, Y., Alam, M.Z. and Hoque, M.R. (2020), "Understanding continuance usage intention of mHealth in a developing country", *International Journal of Pharmaceutical and Healthcare Marketing*, Vol. 14 No. 2, pp. 251–272.

Katheeri, H. Al. (2020), "The Adoption of mHealth Apps Testing the UTAUT Model with Gamification Impact", *AHFE 2020: Advances in Human Factors and Ergonomics in Healthcare and Medical Devices*, pp. 253–259.

Keen, S.M. and Roberts, N. (2017), "Preliminary evidence for the use and efficacy of mobile health applications in managing posttraumatic stress disorder symptoms", *Health Systems*, Vol. 6 No. 2, pp. 122–129.

Kemp, S. (2022), “Digital 2022: Turkey - DataReportal - Global Digital Insights”, *We Are Social*, available at: https://datareportal.com/reports/digital-2022-turkey?rq=2022 turkey (accessed 12 October 2022).

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*, Vol. 78 No. 6, pp. 404–416.

Kim, H., Goldsmith, J. V., Sengupta, S., Mahmood, A., Powell, M.P., Bhatt, J., Chang, C.F., *et al.* (2017), “Mobile Health Application and e-Health Literacy: Opportunities and Concerns for Cancer Patients and Caregivers”, *Journal of Cancer Education*, available at:https://doi.org/10.1007/s13187-017-1293-5.

Klasnja, P. and Pratt, W. (2012), “Healthcare in the pocket: Mapping the space of mobile-phone health interventions”, *Journal of Biomedical Informatics*, Vol. 45 No. 1, pp. 184–198.

Kock, N. and Hadaya, P. (2018), “Minimum sample size estimation in PLS-SEM: The inverse square root and gamma-exponential methods”, *Information Systems Journal*, Vol. 28 No. 1, pp. 227–261.

Kohl, H.W., Craig, C.L., Lambert, E.V., Inoue, S., Alkandari, J.R., Leetongin, G. and Kahlmeier, S. (2012), “The pandemic of physical inactivity: global action for public health”, *The Lancet*, Vol. 380 No. 9838, pp. 294–305.

Kotz, D., Avancha, S. and Baxi, A. (2009), “A privacy framework for mobile health and home-care systems”, *Proceedings of the First ACM Workshop on Security and Privacy in Medical and Home-Care Systems - SPIMACS ’09*, ACM Press, New York, New York, USA, p. 1.

Krebs, P. and Duncan, D.T. (2015), “Health App Use Among US Mobile Phone Owners: A National Survey”, *JMIR MHealth and UHealth*, Vol. 3 No. 4, p. e101.

Lee, H.E. and Cho, J. (2017), “What Motivates Users to Continue Using Diet and Fitness Apps? Application of the Uses and Gratifications Approach”, *Health Communication*, Routledge, Vol. 32 No. 12, pp. 1445–1453.

Leong, L.Y., Hew, T.S., Ooi, K.B. and Wei, J. (2020), “Predicting mobile wallet resistance: A two-staged structural equation modeling-artificial neural network approach”, *International Journal of Information Management*, Elsevier, Vol. 51 No. April 2019, p. 102047.

Lin, W.Y., Zhang, X., Song, H. and Omori, K. (2016), “Health information seeking in the Web 2.0 age: Trust in social media, uncertainty reduction, and self-disclosure”, *Computers in Human Behavior*, Elsevier Ltd, Vol. 56, pp. 289–294.

Liu, D., Maimaitijiang, R., Gu, J., Zhong, S., Zhou, M., Wu, Z., Luo, A., *et al.* (2019), “Using the Unified Theory of Acceptance and Use of Technology (UTAUT) to Investigate the Intention to Use Physical Activity Apps: Cross-Sectional Survey”, *JMIR MHealth and UHealth*, Vol. 7 No. 9, p. e13127.

Lupton, D. (2014), “Apps as Artefacts: Towards a Critical Perspective on Mobile Health and Medical Apps”, *Societies*, Vol. 4 No. 4, pp. 606–622.

Lv, X., Guo, X., Xu, Y., Yuan, J. and Yu, X. (2012), “Explaining the Mobile Health

Services Acceptance from Different Age Groups: A Protection Motivation Theory Perspective", *International Journal of Advancements in Computing Technology*, Vol. 4 No. 3, pp. 1–9.

Mackert, M., Mabry-Flynn, A., Champlin, S., Donovan, E.E. and Pounders, K. (2016), "Health literacy and health information technology adoption: The potential for a new digital divide", *Journal of Medical Internet Research*, Vol. 18 No. 10, pp. 1–16.

Martínez-Pérez, B., de la Torre-Díez, I. and López-Coronado, M. (2015), "Privacy and Security in Mobile Health Apps: A Review and Recommendations", *Journal of Medical Systems*, Vol. 39 No. 1, p. 181.

Mat Zain, N.H., Johari, S.N., Abdul Aziz, S.R., Ibrahim Teo, N.H., Ishak, N.H. and Othman, Z. (2021), "Winning the Needs of the Gen Z: Gamified Health Awareness Campaign in Defeating COVID-19 Pandemic", *Procedia Computer Science*, Vol. 179, pp. 974–981.

Middelweerd, A., Mollee, J.S., van der Wal, C.N., Brug, J. and te Velde, S.J. (2014), "Apps to promote physical activity among adults: A review and content analysis", *International Journal of Behavioral Nutrition and Physical Activity*, Vol. 11 No. 97, pp. 1–9.

Moon, J. and Kim, Y. (2001), "Extending the TAM for a World-Wide-Web context", *Information & Management*, Vol. 38, pp. 217–230.

Moqbel, M., Nevo, S. and Nah, F.F.-H. (2022), "Unveiling the dark side in smartphone addiction: mediation of strain and moderation of hedonic use on well-being", *Internet Research*, available at:https://doi.org/10.1108/INTR-01-2021-0003.

Ndayizigamiye, P., Kante, M. and Shingwenyana, S. (2020), "An adoption model of mHealth applications that promote physical activity", *Cogent Psychology*, Cogent, Vol. 7 No. 1, available at:https://doi.org/10.1080/23311908.2020.1764703.

Nguyen, H.L., Tran, K., Doan, P.L.N. and Nguyen, T. (2022), "Demand for Mobile Health in Developing Countries During COVID-19: Vietnamese's Perspectives from Different Age Groups and Health Conditions", *Patient Preference and Adherence*, Vol. 16, pp. 265–284.

Norman, C.D. and Skinner, H.A. (2006), "eHEALS: The eHealth literacy scale", *Journal of Medical Internet Research*, Vol. 8 No. 4, pp. 1–7.

Nunes, A., Limpo, T. and Castro, S.L. (2019), "Acceptance of Mobile Health Applications: Examining Key Determinants and Moderators", *Frontiers in Psychology*, Vol. 10 No. December, pp. 1–9.

OECD. (2022), "OECD Health Statistics 2022", *OECD Health Database*, available at: https://www.oecd.org/els/health-systems/health-data.htm.

Ökem, Z.G. and Çakar, M. (2015), "What have health care reforms achieved in Turkey? An appraisal of the 'Health Transformation Programme'", *Health Policy*, Vol. 119 No. 9, pp. 1153–1163.

Olla, P. and Shimskey, C. (2015), "mHealth taxonomy: a literature survey of mobile health applications", *Health and Technology*, Vol. 4 No. 4, pp. 299–308.

Phaneuf, A. (2020), "The Number of Health and Fitness App Users Increased 27% from Last Year", *EMarketer*.

Prout Parks, E., Moore, R.H., Li, Z., Bishop-Gilyard, C.T., Garrett, A.R., Hill, D.L., Bruton, Y.P., *et al*. (2018), "Assessing the Feasibility of a Social Media to Promote Weight Management Engagement in Adolescents with Severe Obesity: Pilot Study", *JMIR Research Protocols*, Vol. 7 No. 3, p. e52.

Rahman, M.S., Lakshmikanth, G.S., Chavarria, J.A., Smith, D., Hoque, M.R., Senn, W.D. and Flores, J. (2021), "Toward understanding the technology trust calculus in healthcare: A generation Z and millennial view", *Proceedings of the Annual Hawaii International Conference on System Sciences*, Vol. 2020-Janua, pp. 3514–3523.

Richman, A.R., Webb, M.C., Brinkley, J. and Martin, R.J. (2014), "Sexual behaviour and interest in using a sexual health mobile app to help improve and manage college students' sexual health", *Sex Education*, Vol. 14 No. 3, pp. 310–322.

Ringle, C.M., Sarstedt, M. and Straub, D.W. (2012), "A Critical Look at the Use of PLS-SEM in MIS Quarterly.", *MIS Quarterly*, MIS Quarterly, Vol. 36 No. 1, pp. iiv–8.

del Río-Lanza, A.B., Suárez-Vázquez, A., Suárez-Álvarez, L. and Iglesias-Argüelles, V. (2020), "Mobile health (mhealth): facilitators and barriers of the intention of use in patients with chronic illnesses", *Journal of Communication in Healthcare*, Vol. 13 No. 2, pp. 138–146.

Rogers, E.M. (2003), *Diffusion of Innovations*, 5th ed., Free Press, New York, USA.

Ryan, R.M. and Deci, E.L. (2000), "Intrinsic and Extrinsic Motivations: Classic Definitions and New Directions", *Contemporary Educational Psychology*, Vol. 25 No. 1, pp. 54–67.

Salo, J. and Karjaluoto, H. (2007), "A conceptual model of trust in the online environment", *Online Information Review*, Vol. 31 No. 5, pp. 604–621.

Schoeppe, S., Alley, S., Van Lippevelde, W., Bray, N.A., Williams, S.L., Duncan, M.J. and Vandelanotte, C. (2016), "Efficacy of interventions that use apps to improve diet, physical activity and sedentary behaviour: A systematic review", *International Journal of Behavioral Nutrition and Physical Activity*, Vol. 13 No. 1, available at:https://doi.org/10.1186/s12966-016-0454-y.

Shapiro, L.M. and Kamal, R.N. (2021), "Implementation of Electronic Health Records During Global Outreach: A Necessary Next Step in Measuring and Improving Quality of Care", *The Journal of Hand Surgery*, Vol. In press, available at:https://doi.org/10.1016/j.jhsa.2021.09.016.

Shareef, M.A., Kumar, V. and Kumar, U. (2014), "Predicting mobile health adoption behaviour: A demand side perspective", *Journal of Customer Behaviour*, Vol. 13 No. 3, pp. 187–205.

Sharon, T. (2017), "Self-Tracking for Health and the Quantified Self: Re-Articulating Autonomy, Solidarity, and Authenticity in an Age of Personalized Healthcare", *Philosophy and Technology*, Vol. 30 No. 1, pp. 93–121.

Stone, M. (1974), "Cross-validatory choice and assessment of statistical predictions", *Journal of the Royal Statistical Society*, Vol. 36, pp. 111–147.

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*, Vol. 14 No. 2, pp. 183–200.

Sunyaev, A., Dehling, T., Taylor, P.L. and Mandl, K.D. (2014), “Availability and quality of mobile health app privacy policies”, *Journal of the American Medical Informatics Association*, No. December 2013, pp. 28–33.

Tavares, J. and Oliveira, T. (2016), “Electronic health record patient portal adoption by health care consumers: An acceptance model and survey”, *Journal of Medical Internet Research*, Vol. 18 No. 3, available at:https://doi.org/10.2196/jmir.5069.

Turkish Institute of Statistics. (2021), “Household Information Technology (IT) Use Study, 2021”, available at: https://data.tuik.gov.tr/Bulten/Index?p=Hanehalki-Bilisim-Teknolojileri-(BT)-Kullanim-Arastirmasi-2021-37437 (accessed 12 October 2022).

Turner-McGrievy, G.M., Beets, M.W., Moore, J.B., Kaczynski, A.T., Barr-Anderson, D.J. and Tate, D.F. (2013), “Comparison of traditional versus mobile app self-monitoring of physical activity and dietary intake among overweight adults participating in an mHealth weight loss program”, *Journal of the American Medical Informatics Association*, Vol. 20 No. 3, pp. 513–518.

Venkatesh, V. and Bala, H. (2008), “Technology Acceptance Model 3 and a Research Agenda on Interventions”, *Decision Sciences*, Vol. 39 No. 2, pp. 273–315.

Venkatesh, V., Morris, M.G., Davis, G.B. and Davis, F.D. (2003), “User acceptance of information technology: toward a unified view”, *MIS Quarterly*, Vol. 27 No. 3, pp. 425–478.

Wei, J., Vinnikova, A., Lu, L. and Xu, J. (2021), “Understanding and Predicting the Adoption of Fitness Mobile Apps: Evidence from China”, *Health Communication*, Routledge, Vol. 36 No. 8, pp. 950–961.

Wilson, J., Heinsch, M., Betts, D., Booth, D. and Kay-Lambkin, F. (2021), “Barriers and facilitators to the use of e-health by older adults: a scoping review”, *BMC Public Health*, BMC Public Health, Vol. 21 No. 1, pp. 1–12.

World Health Organization. (2010), *Global Recommendations on Physical Activity for Health*, Geneva, Switzerland.

World Health Organization. (2011), “mHealth: New Horizons for Health through Mobile Technologies.”, *Global Observatory for EHealth Series*, Vol. 3.

Yousef, C.C., Thomas, A., Alenazi, A.O., Elgadi, S., Abu Esba, L.C., AlAzmi, A., Alhameed, A.F., *et al.* (2020), “Adoption of a Personal Health Record in the Digital Age: Cross-Sectional Study”, *Journal of Medical Internet Research*, Vol. 22 No. 10, p. e22913.

Yuan, S., Ma, W., Kanthawala, S. and Peng, W. (2015), “Keep Using My Health Apps: Discover Users’ Perception of Health and Fitness Apps with the UTAUT2 Model”, *Telemedicine and E-Health*, Vol. 21 No. 9, pp. 735–741.

Zaltman, G. and Moorman, C. (1988), “The importance of personal trust in the use of research. - PsycNET”, *Journal of Advertising Research*, Vol. 28 No. 5, pp. 16–24.

Zarnowiecki, D., Mauch, C.E., Middleton, G., Matwiejczyk, L., Watson, W.L., Dibbs, J., Dessaix, A., *et al.* (2020), “A systematic evaluation of digital nutrition promotion websites and apps for supporting parents to influence children’s nutrition”, *The International Journal of Behavioral Nutrition and Physical Activity*, International Journal of Behavioral Nutrition and Physical Activity, Vol. 17 No. 1, p. 17.

Zhang, Y., Liu, C., Luo, S., Xie, Y., Liu, F., Li, X. and Zhou, Z. (2019), "Factors influencing patients' intention to use diabetes management apps based on an extended unified theory of acceptance and use of technology model: Web-based survey", *Journal of Medical Internet Research*, Vol. 21 No. 8, pp. 1–17.

Zhao, Y., Ni, Q. and Zhou, R. (2018), "What factors influence the mobile health service adoption? A meta-analysis and the moderating role of age", *International Journal of Information Management*, Vol. 43 No. December 2016, pp. 342–350.

APPENDIX

Table IV. Measures and items Source: Authors' own work

ID	Item	Source
PERF1	Mobile health apps help me live a healthy life	(Dinev et al., 2016)
PERF2	I believe that mobile health apps are good for me.	
PERF3	Using mobile health apps helps is beneficial for me	
PERF4	I believe it is a good idea to have mobile health apps.	
HEALS	In general, would you say your health is (Poor—Excellent)	
ELIT1	I know how to find helpful health resources on the Internet	(Norman and Skinner, 2006)
ELIT2	I know how to use the Internet to answer my health questions	
ELIT3	I know what health resources are available on the Internet	
ELIT4	I know where to find helpful health resources on the Internet	
ELIT5	I know how to use the health information I find on the Internet to help me	
ELIT6	I have the skills I need to evaluate the health resources I find on the Internet	
ELIT7	I can tell high quality from low quality health resources on the Internet	
ELIT8	I feel confident in using information from the Internet to make health decisions	
TRUS1	There would be reliable third party available to assure the security of the mobile health app.	(Andrews et al., 2014)
TRUS2	I would trust Government to provide ways to protect my personal information in the mobile app.	
TRUS3	I believe that mobile app providers / sponsors would not divulge personal data to other parties without permission.	
TRUS4	I would trust professionals who have authorized access to my mobile app data to properly manage my information.	
TRUS5	App developers and sponsors could be trusted to protect the information on the mobile app.	
PERF1	Using mobile health apps will support critical aspects of my healthcare.	(Tavares and Oliveira, 2016)
PERF2	Using mobile health apps will enhance my effectiveness in managing my health.	
PERF3	Overall, mobile health apps will be useful in managing my healthcare.	
PERF4	Mobile apps will help me in living a healthy life	
EFEX1	Learning how to use Mobile health apps is easy for me.	
EFEX2	My interaction with Mobile health apps is clear and understandable.	
EFEX3	I find Mobile health apps easy to use.	
EFEX4	It is easy for me to become skilful at using mobile health apps.	
SOCI1	People who are important to me think that I should use mobile health apps	
SOCI2	People who influence my behaviour think that I should use mobile health apps	
SOCI3	People whose opinions that I value prefer that I use mobile health apps.	
SOCI4	My friends think that using mobile health apps is a good thing	
FACO1	I have the resources necessary to use mobile health apps.	
FACO2	I have the knowledge necessary to use mobile health apps.	
FACO3	Mobile health apps are compatible with other technologies I use.	
FACO4	I can get help from others when I have difficulties using mobile health apps	
INTE1	I intend to use mobile health apps.	
INTE2	I intend to use mobile health apps in the next months.	
INTE3	I plan to use mobile health apps frequently.	
INTE4	If I have the opportunity, I will use mobile health apps	
PRIV1	I am concerned that the information I submit to mobile health apps could be misused.	(Bansal et al., 2010; Dinev et al., 2016)
PRIV2	I am concerned that a person can find private information about me on the mobile health apps	
PRIV3	I am concerned about providing personal information to mobile health apps, because of what others might do with it.	
PRIV4	I am concerned about providing personal information to mobile health apps, because it could be used in a way I did not foresee.	
ENJY1	Using mobile health apps is fun	(Yuan et al., 2015)
ENJY2	Using mobile health apps is enjoyable	
ENJY3	Using mobile health apps is very entertaining	
USEB1	I use mobile health apps regularly.	(Dwivedi et al., 2016)

Table V. Outer loadings and cross loadings Source: Authors' own work

Item Loadings	ELIT	EFEX	ENJY	FACC	USEB	PERF	PRIV	SOCI	TRUS	INTE
ELIT1	**0.762**	0.281	0.335	0.365	0.093	0.264	-0.097	0.153	0.116	0.180
ELIT2	**0.832**	0.260	0.263	0.407	0.090	0.245	-0.092	0.161	0.129	0.117
ELIT3	**0.867**	0.223	0.331	0.374	0.160	0.228	-0.048	0.177	0.144	0.140
ELIT4	**0.865**	0.197	0.338	0.369	0.148	0.230	-0.052	0.180	0.134	0.129
ELIT5	**0.842**	0.287	0.328	0.442	0.169	0.274	-0.099	0.132	0.180	0.168
ELIT6	**0.847**	0.316	0.264	0.419	0.130	0.243	-0.118	0.111	0.134	0.163
ELIT7	**0.825**	0.290	0.295	0.364	0.181	0.262	-0.091	0.100	0.206	0.123
ELIT8	**0.805**	0.270	0.302	0.357	0.247	0.261	-0.130	0.163	0.226	0.163
EFEX1	0.179	**0.761**	0.210	0.242	0.171	0.260	-0.247	0.190	0.327	0.357
EFEX2	0.247	**0.896**	0.300	0.420	0.179	0.411	-0.405	0.256	0.448	0.438
EFEX3	0.320	**0.889**	0.319	0.480	0.123	0.454	-0.377	0.284	0.359	0.438
EFEX4	0.327	**0.730**	0.260	0.542	0.103	0.343	-0.337	0.193	0.416	0.321
ENJY1	0.325	0.318	**0.900**	0.277	0.342	0.639	-0.246	0.347	0.416	0.560
ENJY2	0.338	0.289	**0.951**	0.287	0.393	0.632	-0.240	0.376	0.392	0.624
ENJY3	0.374	0.324	**0.935**	0.342	0.348	0.672	-0.281	0.367	0.381	0.601
FACC1	0.412	0.398	0.209	**0.809**	0.176	0.275	-0.219	0.111	0.218	0.205
FACC2	0.446	0.427	0.275	**0.887**	0.253	0.322	-0.266	0.182	0.258	0.278
FACC3	0.412	0.386	0.299	**0.853**	0.217	0.338	-0.227	0.123	0.257	0.246
USEB1	0.185	0.176	0.389	0.260	**1.000**	0.282	-0.053	0.285	0.221	0.366
PERF1	0.278	0.436	0.669	0.332	0.284	**0.928**	-0.406	0.371	0.530	0.604
PERF2	0.268	0.362	0.654	0.315	0.322	**0.898**	-0.368	0.331	0.538	0.567
PERF3	0.279	0.453	0.599	0.321	0.284	**0.912**	-0.432	0.309	0.525	0.579
PERF4	0.293	0.407	0.637	0.349	0.290	**0.935**	-0.406	0.354	0.514	0.616
PRIV1	-0.116	-0.458	-0.271	-0.338	-0.052	-0.407	**0.898**	-0.208	-0.560	-0.433
PRIV2	-0.078	-0.399	-0.283	-0.262	-0.048	-0.446	**0.914**	-0.211	-0.598	-0.434
PRIV3	-0.090	-0.283	-0.209	-0.303	-0.078	-0.354	**0.857**	-0.109	-0.424	-0.345
PRIV4	-0.116	-0.296	-0.181	-0.264	-0.005	-0.312	**0.841**	-0.127	-0.425	-0.301
SOCI1	0.226	0.407	0.370	0.310	0.288	0.441	-0.282	**0.776**	0.432	0.531
SOCI2	0.186	0.232	0.318	0.208	0.249	0.320	-0.141	**0.899**	0.377	0.446
SOCI3	0.050	0.142	0.268	0.078	0.191	0.194	-0.116	**0.851**	0.342	0.408
SOCI4	0.113	0.145	0.346	0.075	0.220	0.268	-0.093	**0.850**	0.340	0.494
TRUS1	0.168	0.469	0.372	0.283	0.152	0.556	-0.537	0.351	**0.783**	0.528
TRUS2	0.189	0.446	0.334	0.309	0.123	0.439	-0.375	0.368	**0.800**	0.422
TRUS3	0.141	0.334	0.354	0.234	0.189	0.431	-0.460	0.410	**0.856**	0.442
TRUS4	0.151	0.295	0.343	0.285	0.229	0.395	-0.417	0.321	**0.796**	0.415
TRUS5	0.145	0.375	0.348	0.328	0.218	0.512	-0.572	0.387	**0.884**	0.467
INTE1	0.165	0.455	0.556	0.308	0.318	0.545	-0.411	0.547	0.511	**0.912**
INTE2	0.169	0.436	0.548	0.330	0.266	0.627	-0.417	0.489	0.527	**0.909**
INTE3	0.177	0.475	0.609	0.356	0.334	0.639	-0.457	0.496	0.512	**0.941**
INTE4	0.144	0.340	0.586	0.211	0.395	0.500	-0.284	0.491	0.446	**0.824**