TOWARDS AN INCLUSIVE WORLD: EXPLORING M-HEALTH ADOPTION ACROSS GENERATIONS

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Research Paper

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Abstract

Mobile health (m-health) technologies empower individuals to manage their personal health. Whilst older citizens can benefit greatly from m-health, it remains the case that younger individuals are more likely to use these technologies. However, the factors that drive and inhibit m-health adoption across different age groups remain relatively unexplored. By understanding what drives adoption among different age groups, efforts can be made to meet their needs and increase adoption by all. This study tests whether the predictors of adoption in the technology adoption literature can be extended to the m-health context and whether age serves as a moderator. Our findings suggest that while the extant technology adoption predictors offer insights into adoption decisions, additional constructs would enable a more comprehensive understanding of m-health adoption. The moderating role of age is also supported. Younger individuals are influenced by their expectation of m-health performance, while older individuals are influenced by their perceived ability to use these technologies. M-health technologies should therefore be marketed differently for these age groups and designed to suit their differing needs. This paper highlights the need to educate older citizens to ensure they can take advantage of the benefits offered by m-health and avoid a widening digital divide.

Keywords: m-health digital divide, citizen m-health adoption, m-health technology adoption

1 Introduction

Recent years have seen an explosion in citizens’ adoption of mobile health (m-health) solutions. M-health can be described as the utilisation of mobile technologies such as mobile-based applications to realise health objectives (WHO, 2011). Currently, there are currently in excess of 165,000 m-health applications targeted at citizens (IMS Institute for Healthcare Informatics, 2015) covering a broad scope of health issues ranging from managing a chronic illness to tracking personal fitness. Unsurprisingly, it is often argued that m-health technologies possess the potential to transform healthcare by facilitating the realisation of citizen-centric care, which is heralded to result in better care for patients at lower costs and greater efficiencies (Whittaker 2012). On a practical level, the adoption of m-health solutions by citizens fosters the creation of informed citizens who are more likely to adopt healthy behaviours and are better equipped to manage to their health conditions (Eng and Lee, 2013). The improved management of chronic illness using m-health applications can also lessen associated healthcare costs, resulting in a potential saving of €99 billion on annual healthcare expenditure in the European Union (PWC, 2013). Due to the broad nature of m-health applications, they can be used by almost all individuals with a smartphone. However, it can be argued that some groups stand to benefit more from m-health usage including individuals with chronic conditions and older adults. It was forecast that 500 million people worldwide would use an m-health application in 2015 (PrivacyRights Clearinghouse, 2013). While 19% of all U.S. adults with a smartphone utilised an m-health application in 2012, individuals aged 50 and above were significantly less likely to own a smartphone and to use an m-health application (Fox and Duggan, 2012). In other words, many older individuals do not have the ability to leverage mobile devices and utilise m-health applications, and
those who have this ability are less likely to adopt. This indicates the presence of a digital divide, or a gap between individuals who utilise their ability to exploit the potential of information technologies, and those individuals who do not (Niehaves and Plattfaut, 2013).

The lag in adoption among older adults is worrying, as m-health applications enable individuals to better manage chronic illness (Eng and Lee, 2013) and the incidence of chronic illness increases with age. For example, 62% of Irish citizens over the age of 65 have at least one chronic illness (Nolan and Kenny, 2014). Thus, m-health technologies represent an opportunity for these individuals to better manage their conditions. Exacerbating the problem is the fact that the world’s population is ageing, with the number of people aged 60+ forecast to grow from 12% in 2015 to 22% in 2050 (WHO, 2015). As a result, strategies focusing on healthy and active ageing are being pursued by health agencies across Europe and the Globe. M-health technologies are congruent with those strategies as they can support and increase the adoption of healthy behaviours (Eng & Lee 2013). They can empower older individuals to become more informed and better manage their health, resulting in behaviours synonymous with healthy ageing. Additional benefits include the removal of geographic barriers to accessing health information, the ability to access customised information based on one’s health, and the removal of stigmatisation often associated with other medical devices (Connelly et al, 2006; Cummings, Chau, & Turner, 2009; Whittaker, 2012). In addition, the adoption of m-health by older citizens can result in large savings, both to the individual and to the economy, by reducing trips to the emergency department by 70% and hospital stays by 80% (PWC, 2011).

However, in order to realise these benefits and savings, a number of urgent barriers that inhibit the growth of m-health must be overcome. With citizen interest in m-health beginning to wane (Mottl, 2015), increasing the adoption of these technologies represents one such challenge. It is therefore surprising that despite the fact that the crucial role of citizen acceptance and adoption has been repeatedly highlighted in the literature (e.g. Or and Karsh, 2009; PWC, 2011) and the repeated calls (Agarwal et al., 2010) for research exploring the barriers to citizen adoption of health IT, research examining the factors influencing or inhibiting citizen adoption of m-health remains remarkably limited (Rai et al., 2013). This paper is a response to those calls. It has two aims. Firstly, it has been argued that the technology adoption literature can provide validated and suitable models for examining health IT adoption (Angst & Agarwal 2009). This paper explores whether the extant technology adoption models are suitable for understanding m-health adoption among citizens. Secondly, due to the increasing incidence of chronic illness and co-morbidity among older citizens, they are often viewed as the group with most potential to benefit from m-health use. Their adoption of m-health is therefore critical for the realisation of improved health outcomes and its many benefits including associated massive monetary savings (PWC, 2011). However, research indicates that older citizens are less likely to adopt a m-health physician rating application (Bidmon et al., 2014). The reasons for this resistance and the resulting age-based digital divide remain undetermined. In order to understand this resistance, this paper examines whether age influences the factors that predict adoption of m-health applications. As a result, this paper contributes to the literature by elucidating the factors driving adoption decisions among different age groups, with special emphasise paid to older adults thereby providing insights to guide research in this area as well as practical recommendations for increasing adoption and enabling the realisation of the benefits promised by m-health. It begins by outlining the background to the study, the existing literature is then reviewed to establish current knowledge, a model to explore the presence of an m-health digital divide is presented and quantitatively tested using a sample of 447 citizens in Ireland and the U.S. The findings are outlined and the insights that they provide to our understanding of m-health adoption and the digital divide are discussed. This work represents the first stage in a broader study and aims to test the efficacy of existing models of technology adoption in a m-health context, and elucidate differences based on age. The paper concludes by presenting initial recommendations for stakeholders involved in delivering m-health solutions.
2 Literature Review

2.1 Defining Adoption

This paper is interested in understanding the drivers of m-health application adoption. Adoption is measured using behavioural intention, or an individual’s belief that they will perform the behaviour under examination (Ajzen & Fishbein, 1977). In this paper, the emphasis is on understanding citizens’ intentions to adopt m-health applications in a general sense as opposed to a specific application. There have been recent calls to focus on actual adoption behaviour as opposed to intentions (De Guinea and Markus, 2009). However, it is argued that intentions are sufficient in this paper for three reasons. The first is that, in the technology adoption literature, behavioural intention as a predictor of adoption has received a great deal of theoretical and empirical support with studies finding intention to adopt influenced actual adoption behaviour (Davis, Bagozzi, & Warshaw, 1989; Venkatesh et al., 2003). Second, this paper represents the first component of a broader study and thus focuses on understanding the predictors of adoption intentions. Third, due to low adoption by older citizens and the focus on m-health applications in general, it would not be feasible to measure actual adoption behaviour.

2.2 Measuring Adoption

Since the 1980s, a concerted effort has been made in the technology adoption literature to understand the predictors of technology adoption (Legris et al., 2003). This focus has led to the emergence of numerous models from the technology acceptance model, TAM (Davis 1989) to the theory of planned behaviour, TPB (Azjen 1991). The retesting of these existing models and an effort to culminate the strengths of these models led to the development of the Unified theory of technology acceptance and use, UTAUT by Venkatesh et al. (2003). Predictors of adoption in UTAUT were derived largely from existing models and refined. For example, performance expectancy (PE) is similar to perceived usefulness in TAM and relates to individuals’ belief that the use of the technology will improve their ability to do their job. Effort expectancy bares resemblance to perceived ease of use in TAM and is described as the ease of use associated with the technology. Social influence is similar to subjective norm in TPB and can be explained as individuals’ perception of whether referent others would encourage their use of the technology. Lastly, facilitating conditions relates to individuals’ perceptions of whether technology use is supported within the organisation. UTAUT explained 70% of variance in technology adoption (Venkatesh et al., 2003).

2.3 Measuring Health Technology Adoption

Technology adoption among health professionals has attracted greater attention than citizens. This is unsurprising due to the nascence of technologies enabling the monitoring of health indicators by citizens. It is important to understand the factors influencing m-health adoption in order to ensure the long term success of these technologies and the realisation of the benefits health data can bring (Kim & Park, 2012; Or & Karsh, 2009; Rai et al., 2013). A systematic review of studies exploring patients’ acceptance of health technologies was conducted by Or and Karsh (2009) yielding 52 studies. A number of observations can be made from their findings. Firstly, the majority of studies included in the review examined patients’ acceptance or use of health information websites as opposed to m-health technologies. Again, this is unsurprising due to their nascence. Secondly, 94 potential predictors of adoption were examined. The large number of different factors examined is problematic as it leads to a sporadic body of knowledge which can obfuscate efforts to draw conclusions and can lead to murkiness around what is known and what requires further investigation. A large majority of these factors (67) related to respondent characteristics, with 37 focusing on patients’ health status and 30 deemed socio-demographic factors. This focus on patient factors while important for understanding adopter characteristics, is insufficient in offering a comprehensive understanding of what predicts patient acceptance. Thirdly, many of these studies failed to utilise a guiding theoretical framework or
technology adoption model to aid in variable selection. The review found 7 of the 52 studies utilised TAM variables, 5 of which found PEOU and PU significantly influenced acceptance. Two studies also included self-efficacy finding it was a significant predictor (Or & Karsh, 2009). It is argued that there is a need to examine the efficacy of technology adoption models in predicting m-health adoption among citizens to determine if these models are both applicable and sufficient for understanding m-health application adoption. In line with this assertion, Or and Karsh (2009) called for more complex modelling and the inclusion of models and social factors which were not examined in any study in their review.

2.4 Understanding M-health Adoption

In order to explore the literature further, a review of research published in the Senior Scholars’ basket of eight top IS journals and the top ten Medical Informatics journals according to the 2014 Journal Citation Reports was conducted (Thomson Reuters, 2015). Criteria for acceptance was; articles written in English, published between 1990 and 2016, citizen/patient focus, quantitative, used a technology adoption model. The review identified 11 articles, 7 of which utilised the TAM framework, with 4 adopting UTAUT. A number of observations can be made from this review, which aid in developing a model to test in this paper. Firstly, the findings with regards to the predictors of adoption hypothesised in the original TAM model can be discussed. Davis (1989) originally posited that perceived usefulness (PU) and perceived ease of use (PEOU) influenced intention, with PEOU also predicting PU. Among these studies, Lim et al. (2011) found both PU and PEOU significantly influencing intention, while Lanseng & Andreassen (2007) found PU influenced intention, but PEOU influenced PU. Similarly, Kim & Chang (2006) found that PU influenced user satisfaction (the dependent variable in their study) but PEOU only significantly influenced PU. The same role of PU on intention and insignificant role of PEOU on intention was found by Klein (2007). Regarding the UTAUT variables, all studies found that performance expectancy (PE) influenced intentions (Or et al., 2011; Hsu et al., 2013; Sun et al., 2013; Guo et al., 2013). Perceived behavioural control was not a significant predictor of intention (Or et al., 2011). Effort expectancy (EE) influenced intention in 2 of the 4 studies (Sun et al., 2013; Guo et al., 2013). Social Influence (SI) also influenced intentions in 2 studies (Hsu et al., 2013; Sun et al., 2013). Actual use was influenced by intention and PE in one study (Or et al., 2011). Two other factors examined repeatedly in technology adoption literature can be discussed; self-efficacy and social influence. In this review, two studies examined self-efficacy. They found that health IT self-efficacy influenced PE (Kim & Park, 2012) and self-efficacy influenced PU and PEOU and as a result indirectly influenced intention (Lim et al. 2011). The review by Or and Karsh (2009) found no studies exploring social influence. The current review found that social influence influenced intention in two studies. These findings offer support for the application of technology adoption models to examine health technology adoption by citizens. However, further studies are needed to explore which predictors can be reliably and repeatedly leveraged in this context.

The role of the individual’s health has been measured using various similar variables. Prior illness was found to positively influence PEOU but not PU by Lim et al. (2011). Healthcare need was originally developed and tested by Wilson and Lankton (2004), where it was not a significant predictor of e-health acceptance. However, Klein (2007) found that individuals with higher healthcare needs expressed higher intentions. The mixed results may lead to questions concerning the role of health related variables. However, the sampling followed in these studies is somewhat limited. For instance, Wilson and Lankton (2004) sampled middle aged female patients. Similarly, in the study by Lim et al. (2011) the sample was comprised of Singaporean women. The use of different but similar variables related to health condition can hinder efforts to consolidate findings and make any solid claims in terms of the role of illness on citizens’ acceptance of health technologies. Future studies should seek to justify the choice of health status variable. At this point it is concluded that health variables are conceptually relevant in terms of exploring adoption of health technologies but in need of further exploration. Following their systematic review, Or and Karsh (2009) called for more research into the
conflicting findings of whether poor health status has a positive or negative influence on acceptance. This point is echoed following the findings of our review.

### 2.5 Individual Characteristics: Technology Adoption

Individual characteristics can aid in understanding technology adoption, and have been applied to technology adoption studies in various contexts (e.g. Agarwal & Prasad, 1999). A number of individual factors have been examined in conjunction with the competing technology adoption models. For example, gender, experience, age, and voluntariness are included as moderators in UTAUT. With regards to gender, Venkatesh & Morris (2000) found males were influenced only by perceived usefulness, whereas females were influenced by perceived ease of use, perceived usefulness and subjective norm. This suggests the influence of gender requires more investigation. Voluntariness relates to an individual’s perceptions of whether they have the ability to decide whether or not to adopt the technology (Venkatesh et al., 2003). When testing the moderating role of voluntariness, Venkatesh et al., (2003) found that subjective norm was only significant in situations where adoption was mandatory or not voluntary. Experience relates to the individual’s familiarity with the technology in question, which can start at zero and increase. Experience has been found to influence a number of predictors, with performance expectancy becoming more significant as experience increases and effort expectancy becoming less salient (Venkatesh et al., 2003). Lastly with regards to age, studies have shown that age moderates various predictors of adoption such as perceived behavioural control and subjective norm in TPB (Venkatesh & Morris, 2000).

### 2.6 Individual Characteristics: Health Technology Adoption

The need to include individual characteristics to gain further understanding of technology adoption in the context of health technologies has been highlighted (Kim & Chang, 2006). The findings regarding individual characteristics in Or and Karsh’s (2009) review can first be noted. Among the majority of studies (84%) gender was found to be insignificant, while education level had a positive impact on acceptance in 68% of 28 studies (Or and Karsh, 2009). Prior experience with computers or health technology was positively related to acceptance in 15 of 20 studies (Or and Karsh, 2009). Lastly, age was measured in 39 studies, 26 of which were significant, 19 finding age to be negatively associated with adoption (Or and Karsh, 2009). In the review conducted for this paper, individual characteristics received limited attention. Gender was explored in one study which found males were significantly more likely to adopt a physician rating application (Bidmon et al. 2014). Experience using internet technologies (Bidmon et al. 2014), and using a mobile phone to access health information (Lim et al. 2011) also influenced adoption. Lastly, in terms of age, older individuals were found to be significantly less likely to adopt a physician rating application (Bidmon et al. 2014). Calls for additional examination of demographics have been made, especially in terms of variables yielding mixed results (Or et al. 2011; Rai et al. 2013).

### 3 Proposed Model and Hypotheses

#### 3.1 Predictors of Adoption

As evidenced in the preceding section, the predictors of technology adoption have received mixed results to date in the health context. Each predictor is briefly reviewed at this stage. Firstly, for perceived usefulness or performance expectancy in UTAUT, the majority of existing studies found PE significantly influenced intention and actual adoption behaviour (Or et al., 2011). For instance, Or et al. (2011b) found that PE significantly increased individuals’ intentions and actual use of a web-based self-management solution. Thus it is argued that if individuals believe that m-health applications can aid in the management of their personal health, they will express higher intentions to adopt m-health applications.
**H1:** Performance Expectancy will positively influence m-health application adoption intention. Secondly, effort expectancy or EE has been examined in a number of health technology adoption studies with mixed results. Many studies have supported the link between effort expectancy and performance expectancy. However, some studies have found effort expectancy does not directly influence intention in the health context (Lanseng & Andreassen 2007; Klein 2007). In this context, effort expectancy is similar to self-efficacy, a predictor in TPB. Existing studies have shown self-efficacy significantly influences intention (Or & Karsh, 2009; Kim & Park, 2012) and indirectly via performance expectancy (Lim et al., 2011). In this paper, m-health self-efficacy or MSE is described as an individual’s perceived ability to utilise m-health to manage their personal health. It is argued that self-efficacy makes more conceptual sense in this context, as effort expectancy measures merely if an individual believes the technology is easy to use, whereas self-efficacy measures individuals’ perceived ability to use m-health for the purpose of health management. Thus self-efficacy will be tested not effort expectancy. In the original UTAUT, EE also influenced PE, as if individuals believed a technology was easy to use they were more likely to adopt. Similarly, a previous study conducted in South Korea found that health IT self-efficacy positively influenced PE (Kim and Park, 2012). It is thus argued that m-health self-efficacy will positively influence individuals’ PE, as if individuals believe they can use m-health applications, they are more likely to believe these applications can aid their health management. A positive relationship between MSE and intention is also proposed. UTAUT also includes facilitating conditions as a predictor of adoption. As adoption of m-health technologies takes place outside of any organisation, facilitating conditions is irrelevant in this study.

**H2a:** M-health self-efficacy will positively influence performance expectancy.

**H2b:** M-health self-efficacy will positively influence m-health application adoption intention.

The final predictor of adoption in the UTAUT is social influence or SI, which refers to an individual’s perception of whether referent others would encourage their use of the technology (Venkatesh et al., 2003). Existing research has found that social influence influences performance expectancy (Or et al. 2011; Kim & Park 2012) and intentions to adopt m-health services in China (Hsu et al., 2013; Sun et al., 2013). A similar influence on PE and intention are expected in this study, as if individuals believe referent others such as friends and family would recommend m-health applications, they are more likely to believe that these technologies will aid in managing their health. It is thus hypothesised:

**H3a:** Social Influence will positively influence performance expectancy.

**H3b:** Social influence will positively influence m-health application adoption intention.

### 3.2 Individual Factors

As noted, there is a need for further exploration to determine if and how an individual’s health status can influence their adoption intention. There is also a need to clarify which health variables influence intention. Perceived physical condition has received limited attention with one Chinese study finding it did not influence intentions to adopt m-health (Denga, Moa & Liub, 2014). Healthcare need developed by Wilson and Lankton (2004) has yielded mixed results. It can be argued if individuals have higher healthcare needs, they will express higher intentions to adopt m-health technologies to manage their health (Angst & Agarwal 2009). Conversely, it could be argued that individuals with greater healthcare need might be less willing to adopt due privacy concerns, as individuals with health conditions have been shown to express high health information privacy concerns (Flynn et al., 2003; van Heerden et al., 2013). It is hypothesised that healthcare need will influence intention. Perceived health status has been applied by Bansal, Zahedi, & Gefen (2010) in a privacy study. This variable measures individuals’ perception of their health status as opposed to their need for healthcare services. It is posited that health status will also influence adoption intention.

**H4a:** Healthcare need will influence m-health adoption intention.

**H4b:** Perceived health status will influence m-health adoption intention.
A number of moderators are included in the original UTAUT. In a recent study of physicians’ adoption of a health technology (Electronic medical record systems), Venkatesh, Sykes, & Zhang (2011) argued that age was the only moderator from the original UTAUT pertinent to the health context, and other moderators such as gender and technology experience were not relevant. They found support for the influence of age on the predictors of adoption by physicians. As this paper investigates the presence of a digital divide in m-health adoption, the moderating role of age is explored. This paper is the first to explore the moderating influence of age on the predictors of m-health application adoption intention. It is argued that age will moderate several relationships. Firstly, age has been shown to influence performance expectancy, with PE the strongest predictor of intention among younger individuals (Venkatesh et al., 2003). A similar effect is hypothesised in this paper, as it argued that younger individuals’ intentions to adopt m-health applications will be largely influenced by whether they perceive these applications can aid in their health management.

**H5a:** The relationship between performance expectancy and intention is stronger for younger citizens. Older individuals in contrast, will consider other factors more strongly. Age has been found to positively moderate perceived behavioural control, which is similar to self-efficacy with older workers’ adoption intention influenced more by their perception of behavioural control than younger workers (Morris & Venkatesh 2000). In the context of m-health applications, it is often highlighted that older citizens are less comfortable using mobile devices (IMS Institute for Healthcare Informatics, 2015). It is reasonable to argue that m-health self-efficacy will be more important to older citizens, as younger citizens are far more comfortable using m-health and thus their intentions are less likely to be strongly influenced by self-efficacy. Thus, it is hypothesised that the relationship between SE and adoption intention will be significant for older citizens. Age has been found to moderate the role of social influence, with older individuals influenced more by the views of referent others (Morris & Venkatesh, 2000; Venkatesh et al., 2011). In this context, it is also likely that the view of referent others will strongly influence older citizens’ intentions to adopt m-health applications, compared to younger individuals who will be influenced by their own views of performance expectancy. It is thus hypothesised that the relationship between SI and intention will be significant for older citizens.

**H5b:** The relationship between m-health self-efficacy and intention is stronger for older citizens.

**H5c:** The relationship between social influence and intention is stronger for older citizens.

### 3.3 Proposed Model

These hypotheses are quantitatively explored in the proposed model illustrated below in Figure 1.

![Figure 1. Proposed model](image-url)
4 Methods

4.1 Study Samples, and Collection Methods

As part of a larger study, data was collected from citizens in two countries; the United States and the Republic of Ireland. There are two main reasons for choosing these two countries. First, the use of ICT in the delivery of healthcare services is far more prevalent in the U.S. with 78% of physicians utilising electronic health records in 2013 (Hsiao & Hing 2014). Ireland trails the United States and other European countries in the implementation of ICT in healthcare despite plans to introduce a national electronic health record (Department of Health, 2013). Citizens in Ireland therefore have far less exposure to health ICTs. Second, technology adoption models have been tested numerous times in the U.S. but never in Ireland. Thus, these two countries represent a good means for testing the suitability of these models in determining m-health application adoption. There are also no statistics available which indicate the prevalence of m-health application adoption in Ireland. Several methods to employed to attract respondents. Email invitations were also sent to individuals in alumni groups at both Universities, staff, and individuals who had participated in previous research and had indicated their willingness to partake again. A number of community based programmes run at these Universities for older individuals including health and fitness programmes and educational programmes covering subjects like ICT skills were visited by the researcher to recruit respondents. Individuals who expressed interest could either complete the questionnaire online or via hard copy. A total of 447 complete responses were received (247 Ireland, 202 U.S.). In terms of gender, 61.3% of respondents were female. The sample was subsumed into three categories. The first category represented current students or recent graduates as they represent the group most likely to use m-health applications (Fox and Duggan, 2012). This group was aged between 18-24 and accounted for 25.3% of the total sample. The second group represented employees across various industries. These individuals were aged between 25-49 and accounted for 46.7% of the sample. The last group represented older citizens. The age of 50 was chosen as the cut off point for this group based on the World Health Organisation. This group made up the remaining 28% of the sample. The majority of respondents (57.7%) had completed at least an Undergraduate degree, 28.9% had some college education and the remaining 13.4% had no third level education. In terms of internet experience, 42.8% of respondents indicated they had used the internet for over 15 years, 29% had 10-15 years of experience, 21% had 5-10 years of experience, and the remaining 7% had under 5 years of experience.

4.2 Measurement

Intention to adopt m-health technology was measured by adapting the wording of the intention variable in UTAUT to ensure applicability with the m-health context (Venkatesh et al., 2003). Performance expectancy was measured using 9 items, 6 were derived from the perceived benefits of health technologies measure used by Wilson & Lankton (2004); Wu, Wang, & Lin (2007); Or et al. (2011), the remaining 3 items were added based on feedback when pretesting the instrument among academic experts. Social influence was measured using three items based on UTAUT but adapted to the health context by Or et al. (2011). Self-efficacy was measured using 5 items based on Kim and Park (2012) and Or et al. (2011). Healthcare need was measured using 3 items based on Wilson & Lankton (2004) and health status was measured with 3 items from Bansal et al. (2010). A copy of the instrument is available upon email request to the lead author. The effects of nationality, gender, and experience using similar technologies, are controlled for in this paper due to the focus on age. Email invitations were sent to University students studying across various disciplines at the host institution in Ireland and a large public University in Southwest United States. The instrument was pre-tested among academic staff and PhD students at both institutions and amended based on feedback. The instrument was also pre-tested among 10 Irish citizens of all ages and backgrounds. This pre-test was imperative to ensure descriptions of m-health technologies were comprehensible, questionnaire...
instructions were clear, and all questions could be answered without difficulty. As older respondents struggled with 7 point scales, all scales were reduced to 5 points. The assumptions required for Multivariate analysis were tested following Hair et al. (2010). The skewness and kurtosis of all items was reviewed. None of the items breached the threshold of +/- 2.2 described by George and Mallery (2010). The measurement model was tested using confirmatory factor analysis to determine model fit. The structural model and moderation effects were then tested in AMOS.

5 Analysis: Testing the Measurement model

Confirmatory analysis (CFA) was conducted to test the proposed structure of all constructs. A number of items were dropped due to low loadings. SE2 was dropped from self-efficacy, SI1 from social influence, PE2, PE4, and PE8, the 3 items added during pre-testing of the instrument were dropped from performance expectancy. The wording of all dropped items was clearly different from the other items on the construct, thus adding conceptual support their exclusion. The modification indices were consulted to determine if model fit could be improved. Error terms for SE1 and SE3 were covaried. Model fit statistics indicated good model fit meeting the values recommended by Hair et al. (2010) based on the sample size and number of observed variables in the model. The fit statistics were as follows cmin/df: 2.515, CFI = .958, RMSEA=.058, SRMR=.0571. The next step was to ensure the validity and reliability of the model. Convergent validity was tested by calculating the AVE for all factors. As the AVE for all factors was above .5, the distinct nature of each factor is supported. Discriminant validity was tested by comparing the square root of the AVE with the correlation between each two factors (Hair et al. 2010). All factors met discriminant thresholds as the AVE for each was greater than the correlation values. To test the reliability of the constructs, the CR was calculated. The CR for all factors was above .70 indicating reliability (Performance Expectancy .93, M-health self-efficacy .80, Social Influence .87, Healthcare need .77, Health Status .82, Intention .96). The examination of endogenous and exogenous variables simultaneously using the same sample, can lead to concerns regarding common method bias. Based on recommendations made by Podsakoff et al. (2003), a number of procedural remedies were employed to reduce possible common method bias including ensuring the confidentiality of respondents, assuring respondents there are no right or wrong answers and reducing ambiguity around scale items. Additionally, the single common latent factor approach was used to test for common method bias in AMOS as recommended. A common latent factor was added during confirmatory factor analysis, and standardised regression weights prior to adding the factor were compared to those when the factor was added (Gaskin, 2012b). As none of the standardised regression weights experienced a great change (all deltas were under .200), and all constructs still met the validity and reliability thresholds, common method bias is not a major issue. The common latent factor was thus removed prior to moving forward with the analysis. Due to inclusion of a multi-group moderator (age) in later analysis, the data was tested for metric and configural invariance. Upon constraining the regression weights across all groups, model fit statistics remained adequate indicating the data was configurally invariant. Partial metric invariance was achieved as at least one item for each factor was metrically invariant across the group comparisons (MacKenzie et al., 2011).

5.1 Testing the Hypotheses and Findings

The next stage involved testing the structural model proposed in Figure 1. Composite variables were imputed in AMOS. The structural model also had good fit; cmin/df= 1.970, CFI = .970, RMSEA =.040, SRMR = .0733. Hypotheses testing took place in two stages. The first stage involved testing hypotheses H1-H4b on the overall sample. H1 hypothesised that PE would positively influence intention to adopt m-health applications. This relationship was strongly supported (.402, p<.001). H2a and H2b proposed that m-health self-efficacy would positively influence PE and Intention respectively. The data revealed a positive relationship between MSE and PE (.259, p<.001), thus
supporting H2a. The relationship between MSE and Intention however was negative and insignificant (-.065, n.s.), thereby rejecting H2b. However, self-efficacy did have a significant indirect influence on intention via performance expectancy. This finding echoes that of Lim et al. (2011) who found self-efficacy only influenced intention via performance expectancy. H3a and H3b posited that social influence would positively influence PE and intention respectively. Social influence positively influenced performance expectancy (.643, p<.001) and Intention (.129, p<.05) offering strong support for H3a and H3b. H4a proposed that healthcare need would influence Intention to adopt m-health, this relationship was positive and significant to the .001 level. H4b proposed that poor health status would influence adoption intention, this relationship was negative and insignificant in the data rejecting the hypothesis. These findings are summarised below in Table 1.

<table>
<thead>
<tr>
<th>Hypothesis</th>
<th>Finding</th>
<th>Supported?</th>
</tr>
</thead>
<tbody>
<tr>
<td>H1. Performance Expectancy will positively influence Adoption Intention</td>
<td>(.402) ***</td>
<td>Yes.</td>
</tr>
<tr>
<td>H2a. Self-Efficacy will positively influence Performance Expectancy</td>
<td>(.259) ***</td>
<td>Yes.</td>
</tr>
<tr>
<td>H2b. Self-Efficacy will positively influence Adoption Intention</td>
<td>(-.065) n.s.</td>
<td>No.</td>
</tr>
<tr>
<td>H3a. Social Influence will positively influence Performance Expectancy</td>
<td>(.643) ***</td>
<td>Yes</td>
</tr>
<tr>
<td>H3b. Social Influence will positively influence Adoption Intention</td>
<td>(.129) *</td>
<td>Yes</td>
</tr>
<tr>
<td>H4a. Healthcare Need will influence Adoption Intention</td>
<td>(.248) ***</td>
<td>Yes</td>
</tr>
<tr>
<td>H4b. Health Status will influence Adoption Intention</td>
<td>(-.041) n.s.</td>
<td>No</td>
</tr>
</tbody>
</table>

Table 1. Direct Relationships, **p<.01, *p<.05, n.s not significant to .95% level

For the second stage of analysis, the sample was divided into three groups based on the age categories. The model indicated good fit (cmin/df: 1.364, CFI: .988, SRMR: .048, RMSEA: .029). This stage involved testing multi-group moderation by examining each hypothesis across the age groups and comparing the Zscores between each group to determine if moderation effects were significant. The findings are summarised in Table 2 below and discussed thereafter.

<table>
<thead>
<tr>
<th>Hypothesis</th>
<th>Group 1</th>
<th>Group 2</th>
<th>Group 3</th>
<th>Difference Group 1-2</th>
<th>Difference Group 1-3</th>
<th>Difference Group 2-3</th>
<th>Supported?</th>
</tr>
</thead>
<tbody>
<tr>
<td>5a. The relationship between PE and INT will be stronger for younger citizens (Group1)</td>
<td>(.406) ***</td>
<td>(.413) ***</td>
<td>(.159) n.s</td>
<td>(.0.219)</td>
<td>(-1.152) n.s</td>
<td>(-1.386) n.s</td>
<td>Yes but not significant differences</td>
</tr>
<tr>
<td>5b. The relationship between SE and INT will be strongest for older citizens (Group3)</td>
<td>(.017) n.s</td>
<td>(.0-160) **</td>
<td>(.269)*</td>
<td>(-2.015)*</td>
<td>1.854*</td>
<td>(3.359) **</td>
<td>Yes. Significant differences between groups.</td>
</tr>
<tr>
<td>5c. The relationship between SI and INT will be stronger among older age groups (2&amp;3)</td>
<td>(.018) n.s</td>
<td>(.238) **</td>
<td>(.0-010) n.s</td>
<td>(1.972)*</td>
<td>(-0.107) n.s</td>
<td>(-1.509) n.s</td>
<td>SI was significantly different between groups 1 and 2.</td>
</tr>
</tbody>
</table>

Table 2. Findings: Moderation. Note: **p<.001, *p<.01, *p<.05, n.s not significant to .95% level

Performance expectancy had the greatest influence among the youngest age group as expected supporting H5a. However, the differences in performance expectancy between other age groups were not significant. The insignificant nature of the PE-INT relationship among older adults is surprising, as previous studies have found that perceived usefulness and perceived value influences intentions

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among this group (Hsu et al., 2013; Deng et al., 2014). The direct relationship between self-efficacy and intention was insignificant in the youngest group unsurprisingly. However, self-efficacy indirectly influenced intention via performance expectancy for group 1. This relationship was significant for group 2 and group 3, supporting H5b. However, the direction of this relationship was opposite than hypothesised. Self-efficacy had a negative influence on intention among individuals aged 25-54, but a positive influence on intention among individuals aged 50 and over. One explanation for this difference may be difference in experience levels. As older individuals have lower levels of experience using mobile devices for the purpose of maintaining their health, self-efficacy may play a bigger role. Individuals in the second age group on the other hand are likely to have a greater deal of experience with using technology for health purposes. If the majority believe they could use the technologies with ease, they may be unlikely to be largely affected by this ability and more influenced by other factors such as performance expectancy. Older citizens may be too preoccupied by their ability to use the technologies to consider other factors such as performance expectancy. Social influence was also significant among the second age group, with a significant difference evident between this group and the younger group. Social influence did however, have an indirect influence on intention via PE. The analysis also focused on determining the role of health variables in influencing intention across different age groups. Healthcare need significantly influenced intention among age groups 2 and 3, with a stronger influence among group 3 (.236*). This is unsurprising as we expect individuals in this age group to have a higher need for healthcare services. The positive nature of this relationship supports previous findings (Klein, 2007), with individuals with higher healthcare needs expressing higher intentions to use these technologies. The second health variable was perceived (poor) health status which was only significant among group 3 and had a negative influence on intention. In other words, individuals who indicated they were of poor health were less likely to adopt m-health technologies. The difference in relationship between these health variables and intention indicate that they are distinct and give us different insights into adoption decisions. Individuals with a higher need for healthcare services are more likely to use m-health, but individuals with poor health are less likely to adopt. It may be that these individuals do not believe m-health can aid in managing their condition.

6 Discussion

This study examined whether the predictors of adoption as identified in the technology adoption literature can be extended to the context of m-health and whether age serves as a moderating variable in that context. Predictors of adoption from both UTAUT and TPB were included in a model that was then used to explore the predictors of m-health adoption intention. Among the overall sample, the model explained 65.5% of variance in PE and 41% in adoption intention. The moderating role of age on these relationships and the influence of health variables on intention were also tested to explore the presence of a digital divide in m-health adoption. This model was tested among 447 Irish and U.S. citizens. The second model explained 41% variance in adoption intention and 57% variance in performance expectancy among group 1 (18-24 year olds), 49.4% variance in adoption intention and 63% variance in performance expectancy among group 2 (25-49 year olds) and 41% variance in adoption intention and 79% variance in performance expectancy among group 3 (50+ year olds). This variance is similar to Venkatesh et al. (2011) who found UTAUT explained 44% variance in doctors’ intentions to use electronic medical record systems. This study makes four main contributions to MIS and Medical Informatics research. Firstly, among young adults, performance expectancy emerged as the strongest predictor of adoption, with self-efficacy and social influence indirectly influencing adoption decisions. The fact that younger adults would focus on performance expectancy is not surprising as they have greater experience using technology and a corresponding focus on its benefits. However, what is surprising is the insignificant nature of the relationship between performance expectancy and intention to use among older adults, particularly as previous studies have found that perceived usefulness strongly influences intentions among this group (Sun et al., 2013; Deng et al. 2014). This study provides evidence that this is not
always the case in the context of m-health technology adoption and highlights the fact that the relationship between performance expectancy and intention to use cannot be taken for granted and may vary according to the health technology and population under consideration. Secondly, the study findings show that for individuals aged 25-49 years, performance expectancy and social influence both drive adoption decisions with self-efficacy negatively influencing intentions. It is not surprising that younger individuals are not influenced by the views of referent others as their decision is based largely on their belief of whether the application will aid them in managing their health. This finding extends previous findings to the health context illustrating that the views of referent others does not exert a significant influence on the adoption intentions of younger adults (Morris & Venkatesh 2000). It is interesting that social influence was insignificant among individuals aged 50 and over. However, this may partly be explained by the dominant role of self-efficacy, regardless of the views of referent others, individuals in this age group base their intentions on whether they feel they are capable of using these technologies.

Thirdly, distinct evidence of a digital divide was found. Age significantly moderated the influence of m-health self-efficacy on adoption intentions. The third group of individuals aged 50+ were influenced most by self-efficacy suggesting that many in this group currently lack an ability to adopt m-health technologies and their perceived inability to use m-health outweighs the views of referent others and performance expectancy. Until that inability is addressed, m-health technologies are likely to suffer from lack of uptake regardless of the benefits that they can confer. The fourth and final contribution relates to clarification on the role of health variables. Health-related variables did not influence younger people in this study sample. However, among the older age groups, greater healthcare need resulted in increased intentions, while poorer health status reduced adoption intentions among the oldest group. The fact that greater healthcare need results in increased intention to adopt is unsurprising, but points to the fact that older adults experiencing initial health problems may be open to interventions to help them utilise m-health applications to manage their health conditions.

The findings offer useful practical insights showing that different age groups’ intentions to adopt m-health technologies are influenced by different factors. Thus these technologies should be presented to them in ways that appeal to these influencers. The influencers of intention should be considered when marketing and designing m-health technologies, especially if a specific age group is being targeted. For example, younger individuals are influenced by how useful the technology is in managing health. Therefore, the benefits or uses of these technologies should be highlighted when attempting to attract the youngest age group. The second age group will also be influenced by performance expectancy and the view of referent others. Marketing campaigns should consider combining the two factors and highlight the uses of m-health, whilst including testimonials of similar individuals using m-health. Lastly, individuals aged 50 and above are influenced predominately by their ability to use m-health. This points to a digital divide that is based on perception of ability to use the technology. Therefore, the prevalence of lower experience levels and low self-efficacy should be considered in designing and communicating m-health technologies for this age group. Improving self-efficacy among this age group is particularly important as older citizens can benefit greatly from m-health. However, if they don’t feel equipped to adopt these technologies, then they will not do so. Over time, if this lack of confidence in using m-health technologies remains unaddressed, it is likely to deepen the digital divide. This would result in social problems and an increased financial burden on the State due to the ageing population and the increasing incidence of chronic illness among this age group (Nolan & Kenny, 2014). In order to avoid a widening digital gap in m-health adoption, large-scale educational efforts may be required. These efforts could incorporate various bodies including health professionals to promote the benefits and perhaps government to highlight some recommended trustworthy applications. Educational institutions and organisations focused on the ageing community could offer courses in using m-health, the aim being to improve self-efficacy and promote the adoption of m-health technologies to manage health and illness. Such courses may vary depending on the type of m-health technology in question i.e. solutions targeting specific conditions such as diabetes and solutions which encourage healthy behaviours. As m-health solutions are not a silver bullet to improving one’s
health or health management, educational efforts should go beyond the usability aspects and educate users on the security, privacy, and credibility risks associated with use, provide citizens with the digital and privacy literacy skills needed to confidently utilize these solutions, while also cautioning against overreliance on these solutions to manage one’s health conditions.

The limitations of the study can be noted. Firstly, adoption intention was measured but not actual adoption. While future research should explore actual m-health adoption, previous studies have shown intention predicts adoption in this context (Or et al. 2011) and as such intention provides valuable insights in this study which can be further explored and developed in future research. There are some limitations within the existing samples owing to the focus on two highly industrialised countries and the recruitment of respondents with some association to the two chosen Universities, for older adults this association was either through participation in prior research or University-based exercise and educational programmes. It would be interesting to continue the work of researchers such as Sun et al. (2013) in exploring adoption outside of the Western context. With a larger sample the middle age group and the older age group could be each divided into two groups to explore differences within. The large majority of individuals in the study had some experience with the internet and mobile devices. In order to further explore the digital divide, the inclusion of more individuals with varying educational backgrounds and individuals with less or no Internet experience could yield interesting results. This study also focuses on m-health applications in a broad sense as opposed to one solution.

The latter stages of this study apply qualitative methods of inquiry to discern which types of applications are influenced most by these predictors among the different age cohorts and nationalities. In addition, future research could leverage samples associated with health organisations such as hospitals or doctors’ offices to investigate the adoption decisions of different age groups towards applications which target specific health conditions thereby building on the work of researchers such as Bidmon et al. (2014). Such work could also delve into the differences in usage between voluntary adoption decisions and adoption based on recommendation by a healthcare professional.

There are also many additional opportunities to further explore this area. Findings show healthcare need and health status influence intention in different ways, the reasons behind this could be explored qualitatively. It is also argued that these age groups could be studied separately in depth. For the younger group, the influence of performance expectancy would be unpacked further to explore its sustained influence post adoption and to determine whether individuals’ decisions to maintain use are influenced by their perceptions of the application performance to date or just their perception of the potential performance. For the middle group, the negative influence of self-efficacy can be explored further. For the third group, it is suggested that other factors might influence adoption such as privacy concerns or trust (Or et al. 2011). To further understand the impact of these predictors on individuals’ adoption decisions and subsequent usage and identify other possible predictors, qualitative exploration may prove fruitful. The role of additional factors such as privacy and trust is explored in the latter stages of this study.

7 Conclusion

This paper provides both practical contributions and empirical advancements to the literature in MIS and Health Informatics. It supports the extension of technology adoption models such as UTAUT and TPB to measure citizens’ intentions to adopt m-health and provides evidence that intentions to adopt m-health are influenced by different factors depending on respondents’ age. The importance of self-efficacy among older citizens illustrates that the digital divide may prevail in this context. While many of these individuals can use mobile devices, the extension of using these devices for health purposes presents many challenges. Many may perceive they do not have the ability to do so. Thus, the need to fully educate this group in relation to m-health use, its benefits, and other possible issues such as trust and privacy is imperative to ensuring its successful adoption. The next stages of this work explore these issues while also engaging in deeper investigations into the influence of different factors on the adoption decisions and subsequent usage patterns of differing age groups in both countries.

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References


