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APPLYING UTAUT2 TO EXPLAIN THE USE OF PHYSICAL ACTIVITY LOGGER APPLICATIONS AMONG YOUNG ELDERLY

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Abstract Digital wellness technologies have been proposed as a promising way to promote the levels of physical activity and to solve the prevalent problem of physical inactivity among elderly people. In this study, we propose and test a research model for explaining the acceptance and use of these technologies in the case of the young elderly segment (people aged 60–75 years) and physical activity logger applications. The proposed model is theoretically founded on UTAUT2, and it is empirically tested by using the data collected from 115 Finnish young elderly users of a physical activity logger application and analysed with partial least squares based structural equation modelling (PLS-SEM). We find habit to act as the strongest antecedent of use intention, followed by performance expectancy and hedonic motivation with approximately equally strong effects. In contrast, the effects of effort expectancy and social influence on use intention were found as statistically not significant.

Ključne besede: physical activity logger applications, young elderly, UTAUT2, digital wellness technologies, partial least squares.

1 Introduction

In the recent years, failing to meet the recommendations for adequate amounts of physical activity has become a prevalent problem among elderly people (Sun, Norman & While, 2013). Therefore, new and innovative ways to promote the levels of physical activity in this segment are urgently needed. One potential way to achieve this are different types of digital wellness technologies, such as smartphone and smartwatch applications, which have been found very promising in terms of promoting the levels of physical activity not only among young but also among elderly people (e.g., Changizi & Kaveh, 2017; Muellmann et al., 2018; Elavsky, Knapova, Klocek & Smahel, 2019; Stockwell et al., 2019; Yerrakalva, Yerrakalva, Hajna & Griffin, 2019), although more high-quality studies especially on their long-term effects are still called for. In addition to elderly people in general, their potential has also been highlighted in the more specific segment of young elderly, which consists of people aged approximately 60–75 years (e.g., Carlsson & Walden, 2015–2019; Carlsson & Carlsson, 2016; Walden & Sell, 2017; Allmér, 2018).

However, despite their promising status as a solution for the aforementioned inactivity problem, there is a severe lack of prior studies on the antecedents of the acceptance and use of digital wellness technologies among elderly people, which can be considered a serious shortcoming in both theoretical and practical terms. The objective of the present study is to address this gap in prior research by proposing and testing a research model for explaining the phenomenon in the case of the young elderly segment and one common type of digital wellness technology: physical activity logger applications. By *physical activity logger applications*, we refer to mobile applications that enable users to log and keep track of their physical activities as well as view different types of reports about them. The data about the physical activities may be entered to the application manually by the users or it may be measured automatically by the application itself or by other applications or devices, from which it is then transferred to the application in question. The application may also act as an aggregator that extracts the data from multiple different sources. The theoretical foundation of the proposed model is based on UTAUT2 by Venkatesh, Thong, and Xu (2012). The model is empirically tested by using the data collected from 115 Finnish young elderly users of a physical activity logger application and analysed with partial least squares based structural equation modelling (PLS-SEM).

After this introductory section, we describe in more detail the research setting and the research model of the study in Sections 2 and 3. This is followed by a description of the research methodology and reporting of the research results in Sections 4 and 5. The results will be discussed in more detail in Section 6. Finally, we will conclude the paper with a brief discussion about the limitations of the study and potential paths of future research in Section 7.

2 Research Setting

This study was conducted as part of a broader research program that uses digital wellness technology to study and promote the physical activity of young elderly in Finland. The multiyear and nationwide program is conducted in close co-operation with Finnish pensioners' associations, which are responsible for recruiting volunteer participants to the program amongst their members. The interaction between the researchers and the participants takes place mainly in group meetings of about 20–50 participants, in which typically one or two researchers present the participants information about the program and collect data through surveys. The first three of these group meetings take place during the first few weeks of participation. This is followed by multiple successive self-monitoring periods of about four months, during which the participants are asked to use a physical activity logger application to collect data about their actual physical activity. At the end of each self-monitoring period, there is another group meeting. The application, like participating in the program itself, is totally free for the participants. However, all the participants are required to own a smartphone on which the application can be installed.

The application is available for both Google's Android and Apple's iOS operating systems, and it is developed by the research program itself on top of the Wellmo (2020) platform. In the group meetings, the participants are trained to use the application and instructed to conduct the logging manually by entering the type, intensity, time, and duration of their physical activities. The application also has the ability to extract the data about the physical activities automatically from other applications, such as Google Fit and Apple Health. However, in the group meetings, the participants are not trained or instructed to take this feature into use, which is why few are likely to use it. Based on the logged data, the application shows the users different types of reports about their physical activities.

3 Research Model

The research model of the study is based on UTAUT2 by Venkatesh et al. (2012), which is an extension of the unified theory of acceptance and use of technology (UTAUT) by Venkatesh, Morris, Davis, and Davis (2003) from organisational to consumer contexts. UTAUT2 has been applied to explain technology acceptance and use in numerous information systems (IS) contexts, including also the context of mobile health and fitness applications and devices (e.g., Yuan, Ma, Kanthawala & Peng, 2015; Beh, Ganesan, Iranmanesh & Foroughi, 2019; Dhiman, Arora, Dogra & Gupta, 2019; Duarte & Pinho, 2019; Talukder, Chiong, Bao & Malik, 2019) and the context of elderly users (e.g., Macedo, 2017). However, no prior studies that we are aware of have combined these two contexts by studying, for example, the acceptance and use physical activity logger applications among young elderly, as it is done in the present study.

In UTAUT2, the behavioural intention to use a particular technology is hypothesised to be positively affected by seven antecedent constructs (Venkatesh et al., 2012): *performance expectancy* (i.e., the degree to which using a technology will provide benefits to consumers in performing certain activities), *effort expectancy* (i.e., the degree of ease associated with consumers' use of technology), *social influence* (i.e., the extent to which consumers perceive that important others believe they should use a particular technology), *facilitating conditions* (i.e., consumers' perceptions of the resources and support available to perform a behaviour), *hedonic motivation* (i.e., the fun or pleasure derived from using a technology), *price value* (i.e., the consumers' cognitive trade-off between the perceived benefits of the technology and the monetary cost for using it), and *habit* (i.e., the extent to which people tend to perform behaviours automatically because of learning). In addition, UTAUT2 also introduces three moderators for the effects of these seven antecedent constructs on use intention: *age*, *gender*, and *experience*. However, because of the limited number of participants in our research program at the time of conducting the present study, these moderators are omitted in our research model. In addition, we also omit two of the seven antecedent constructs: facilitating conditions and price value. These were considered irrelevant in the current research setting because all the participants had identical resource requirements for participating in the program (i.e., owning a smartphone) and were given identical training and support for installing and using the physical activity logger application. In addition, as already mentioned above, the application was totally free for all the participants. Finally, our research model also concentrates on explaining only use intention and not actual use behaviour. The research model, with the omitted constructs and effects presented as dashed, is illustrated in Figure 1.

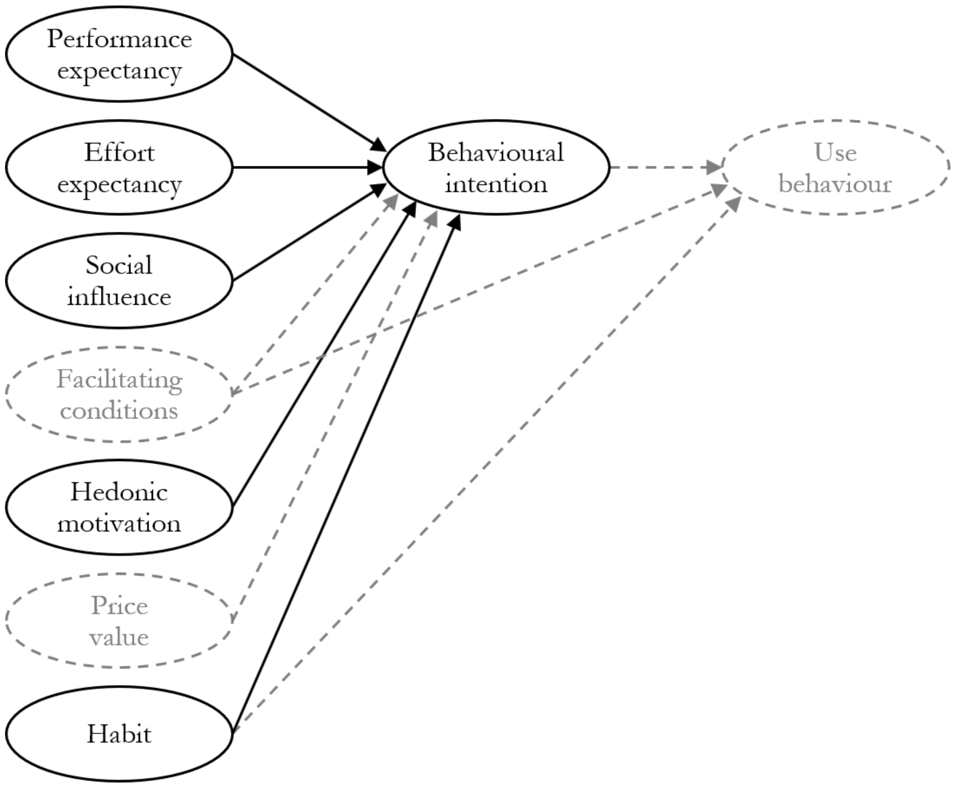

Figure 1: Research model (the dashed constructs and effects are omitted in this study)

4 Methodology

The data for the study was collected from the participants of our aforementioned research program with pen-and-paper questionnaires in the group meetings that were arranged in autumn 2019 after the first four-month self-monitoring period. Because Finland has two official languages, the participants had the option to response to the questionnaire in either Finnish or Swedish. In the questionnaire, each construct of the research model was measured reflectively by three indicators, which were all adapted from the study by Venkatesh et al. (2012). The wordings of these indicators in English are reported in Table 1. The measurement scale of the indicators was a seven-point Likert scale ranging from one (strongly disagree) to seven (strongly agree). In addition, the participants also had the option not to respond to a particular item, which resulted in a missing value.

Table 1: Indicator wordings (PE = performance expectancy, EE = effort expectancy, SI = social influence, HM = hedonic motivation, HT = habit, BI = behavioural intention)

Indicator	Wording
PE1	I find the app useful in achieving my daily exercise goals.
PE2	Using the app helps me achieve my exercise goals more quickly.
PE3	Using the app increases my efficiency in achieving my exercise goals.
EE1	Learning how to use the app to achieve my exercise goals is easy for me.
EE2	I find using the app to achieve my exercise goals easy.
EE3	It is easy for me to become skilful at using the app to achieve my exercise goals.
SI1	People who are important to me think that I should use the app to achieve my exercise goals.
SI2	People who influence my behaviour think that I should use the app to achieve my exercise goals.
SI3	People whose opinions I value prefer that I use the app to achieve my exercise goals.
HM1	Using the app to achieve my exercise goals is fun.
HM2	Using the app to achieve my exercise goals is enjoyable.
HM3	Using the app to achieve my exercise goals is entertaining.
HT1	The use of the app to achieve my exercise goals has become a habit for me.
HT2	I am addicted to using the app to achieve my exercise goals.
HT3	I must use the app to achieve my exercise goals.
BI1	I intend to continue using the app to achieve my exercise goals.
BI2	I will always try to use the app to achieve my exercise goals.
BI3	I plan to use the app regularly to achieve my exercise goals.

Due to the relatively small sample size, the collected data was analysed with variance-based structural equation modelling (VB-SEM), more specifically partial least squares (PLS), by using the SmartPLS version 3.2.9 software by Ringle, Wende, and Becker (2015). When running the analyses and reporting the results, we followed the guidelines given by Hair, Hollingsworth, Randolph, and Chong (2017) for IS research. For example, in the model estimation, we used mode A as the indicator weighting mode of the constructs, path weighting as the weighting scheme, and +1 as the initial weights, while the statistical significance of the model estimates was tested by using bootstrapping with 2,500 subsamples and individual sign changes. As the threshold for statistical significance, we used $p < 0.05$. The potential missing values were handled by using mean replacement.

5 Results

We received valid responses from a total of 115 participants. The descriptive statistics of this sample in terms of the gender, age, and response language of the participants as well as their subjective assessment of own level of physical activity are reported in Table 2. As can be seen, nearly two-thirds of the respondents were women, and nearly nine out of ten assessed their level of physical activity as either moderate or higher. The age of the respondents ranged from 49 to 80 years, with a mean of 69.3 years and a standard deviation 5.0 years. A vast majority of the respondents belonged to the young elderly segment, but there were also a few respondents who were slightly younger or older than our target segment consisting of people aged approximately 60–75 years. However, we decided not to drop these respondents from the study due to our relatively small sample size.

Table 2: Sample statistics (N = 115)

	N	%
Gender		
Man	43	37.4
Woman	72	62.6
Age		
Under 60 years	3	2.6
60–64 years	11	9.6
65–69 years	44	38.3
70–74 years	39	33.9
75 years or over	18	15.7
Language		
Finnsh	69	60.0
Swedish	46	40.0
Level of physical activity		
Very high	1	0.9
High	18	15.7
Moderate	84	73.0
Low	4	3.5
Very low	8	7.0
Totally passive	0	0.0

5.1 Estimation Results

Estimation results of the model in terms of the size and statistical significance of the standardised path coefficients as well as the proportion of explained variance in the behavioural intention construct are reported in Figure 2. Of the five antecedent constructs, performance expectancy, hedonic motivation, and habit were found to have a positive and statistically significant effect on behavioural intention, whereas the effects of effort expectancy and social influence were found to be statistically not significant. Together, the five antecedent constructs were found to explain about 73.5% of the variance in behavioural intention.

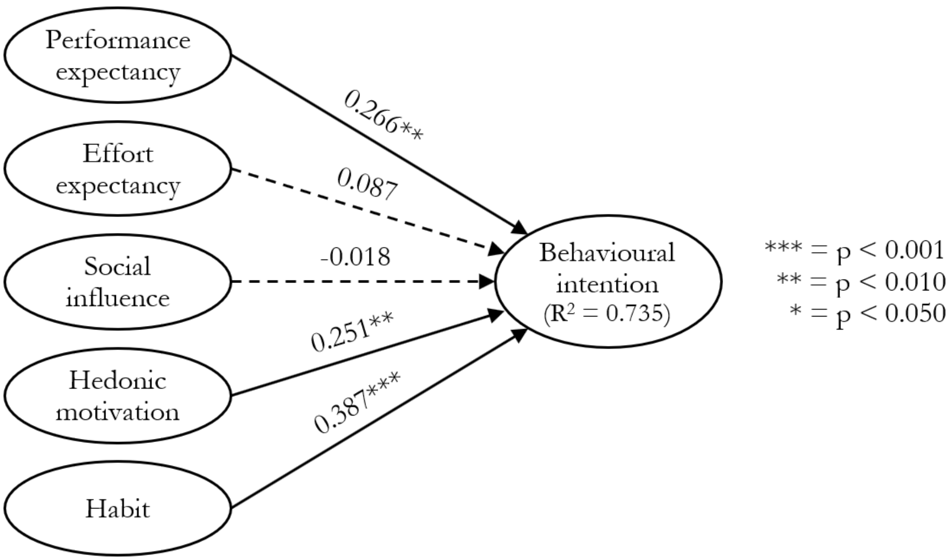

Figure 2: Estimation results

In the following two subsections, the reliability and validity of the estimated model is examined in more detail at the level of both constructs and indicators.

5.2 Construct Reliability and Validity

Construct reliabilities were evaluated by using the composite reliabilities (CR) of the constructs (Fornell & Larcker, 1981), which are commonly expected to be greater than or equal to 0.7 (Nunnally & Bernstein, 1994). The CR of each construct is reported in the first column of Table 3. As the reported values show, all the constructs met this criterion. In turn, construct validities were evaluated by examining the convergent and discriminant validities of the constructs by using the two criteria proposed by Fornell and Larcker (1981). Both of them are based on the average variance extracted (AVE) of the constructs, which refers to the average proportion of variance that a construct explains in its indicators.

Table 3: Construct statistics (CR = composite reliability, AVE = average variance extracted)

Construct	CR	AVE	PE	EE	SI	HM	HT	BI
PE	0.906	0.763	0.873					
EE	0.849	0.654	0.426	0.809				
SI	0.923	0.800	0.548	0.250	0.894			
HM	0.927	0.809	0.680	0.448	0.495	0.900		
HT	0.849	0.653	0.719	0.479	0.466	0.772	0.808	
BI	0.928	0.812	0.743	0.494	0.454	0.761	0.806	0.901

In order to exhibit satisfactory convergent validity, the first criterion expects that each construct should have an AVE of at least 0.5. This means that, on average, each construct should explain at least half of the variance in its indicators. The AVE of each construct is reported in the second column of Table 3. As the reported values show, all the constructs met also this criterion. In order to exhibit satisfactory discriminant validity, the second criterion expects that each construct should have a square root of AVE greater than or equal to its absolute correlation with the other constructs in the model. This means that, on average, each construct should share at least an equal proportion of variance with its indicators than it shares with these other constructs. The square root of AVE of each construct (on-diagonal cells) and the correlations between the constructs (off-diagonal cells) are reported in the remaining columns of Table 3, showing that this final criterion was also met by all the constructs.

5.3 Indicator Reliability and Validity

Indicator reliabilities and validities were evaluated by using the standardised loadings of the indicators, which are reported in Table 4 together with the mean and standard deviation of each indicator as well as the percentage of missing values. In the typical case where each indicator loads on only one construct, it is commonly expected that the standardised loading of each indicator is statistically significant and greater than or equal to 0.707 (Fornell & Larcker, 1981). This is equal to the standardised residual of each indicator being less than or equal to 0.5, meaning that at least half of the variance in each indicator is explained by the construct on which it loads. The only indicator that did not meet this criterion was EE3. However, also its standardised loading of 0.688 was very close to the 0.707 threshold and clearly above the 0.4 threshold, which has been proposed in some prior guidelines for IS research (e.g., Gefen, Straub & Boudreau, 2000). Therefore, and because no issues were found in the reliability and validity of the effort expectancy construct, we decided not to drop this indicator from the model.

Table 4: Indicator statistics (SD = standard deviation, *** = p < 0.001)

Indicator	Mean	SD	Missing	Loading
PE1	5.468	1.619	5.2%	0.889***
PE2	5.020	1.761	12.2%	0.866***
PE3	5.083	1.658	6.1%	0.865***
EE1	6.195	1.301	1.7%	0.849***
EE2	6.027	1.268	3.5%	0.876***
EE3	5.640	1.488	3.5%	0.688***
SI1	4.135	2.196	22.6%	0.933***
SI2	4.476	2.127	28.7%	0.923***
SI3	5.202	1.841	22.6%	0.824***
HM1	5.566	1.324	7.8%	0.906***
HM2	5.660	1.310	10.4%	0.883***
HM3	4.892	1.723	11.3%	0.911***
HT1	5.879	1.558	7.0%	0.828***
HT2	4.029	2.041	10.4%	0.730***
HT3	4.848	1.920	8.7%	0.860***
BI1	5.569	1.755	11.3%	0.906***
BI2	5.214	1.696	10.4%	0.868***
BI3	5.570	1.677	7.0%	0.928***

6 Conclusions

In this study, we proposed and tested a research model based on UTAUT2 for explaining the use intention of physical activity logger applications among young elderly. Despite omitting some of the constructs and moderators of the original UTAUT2, we found the model to explain as much as about 73.5% of the variance in use intention. More specifically, its estimation results suggested three main findings. First, by far the strongest antecedent of the intention to use physical activity logger applications among young elderly seemed to be habit. Second, based on the statistically significant and approximately equally strong effects of performance expectancy and hedonic motivation on use intention, it seemed that the motivation to use physical activity logger applications among young elderly was driven by both utilitarian and hedonic considerations about their use. Third, based on the statistically not significant effects of effort expectancy and social influence on use intention, it seemed that the perceived ease of use of physical activity logger applications or the perceived opinions of important others about their use were not that relevant for young elderly in terms of their use motivation.

From a theoretical perspective, when reflecting the aforementioned findings to the hypotheses of UTAUT2, the first finding concerning the effect of habit cannot be considered as particularly surprising because habit is hypothesised to have a stronger effect on behavioural intention in the case of older people, whereas the effects of performance expectancy and hedonic motivation on behavioural intention are hypothesised to be stronger in the case of younger people. In contrast, the third finding concerning the effects of effort expectancy and social influence can be seen as more surprising when considering that UTAUT2 hypothesises that the effects of effort expectancy and social influence on behavioural intention should also be stronger in the case of older people, particularly older women who constituted the majority of our study sample. In turn, when reflecting our findings to those of prior studies that have applied UTAUT2 to the context of mobile health and fitness applications and devices (e.g., Yuan et al., 2015; Beh et al., 2019; Dhiman et al., 2019; Duarte & Pinho, 2019; Talukder et al., 2019) as well as to the context of elderly users (e.g., Macedo, 2017), the most important and interesting conflict concerns the relative strengths of performance expectancy, hedonic motivation, and habit as antecedents of use intention. That is, prior studies (e.g., Yuan et al., 2015; Macedo, 2017; Duarte & Pinho, 2019) have typically found performance expectancy to act as clearly the strongest antecedent of use intention, whereas hedonic motivation and habit have typically been found to have approximately equally strong but weaker effects. In contrast, in our study, the roles of performance expectancy and habit seem to have been swapped, with habit acting as clearly the strongest antecedent of use intention and performance expectancy and hedonic motivation having approximately equally strong effects. The main exception to this is the study by Talukder et al. (2019), which also found habit to have the strongest effect on the use intention of wearable fitness devices. However, in their study, performance expectancy was found to have an approximately equally strong effect as habit, whereas hedonic motivation was found to have no statistically significant effect on use intention. Finally, in terms of the statistically not significant effects of effort expectancy and social influence found in our study, some prior studies have made similar findings (e.g., Yuan et al., 2015; Duarte & Pinho, 2019), whereas others have found the effect of either effort expectancy (Macedo, 2017; Beh et al., 2019) or both effort expectancy and social influence (Dhiman et al., 2019; Talukder et al., 2019) as statistically significant, although in most cases as relatively weak.

From a practical perspective, the findings of the study offer the providers of physical activity logger applications, and potentially also the providers of other types of digital wellness technologies that are targeted at promoting the physical activity of young elderly, some valuable insights on technology acceptance and use. First, it is critical that the potential users can easily integrate the applications as part of their everyday practices and make their use habitual. If the use becomes habitual, then it is very likely to continue also in the future. Second, it is not enough for the providers to develop their applications with only utility and performance aspects in mind, but the applications should also be fun to use. Two examples of the approaches that can be used to achieve this goal are gamification (e.g., Kari, Piippo, Frank, Makkonen & Moilanen, 2016; Koivisto & Hamari, 2019) and exergaming (e.g., Kari, 2014; Kari & Makkonen, 2014; Kappen, Mirza-Babaei & Nacke, 2019). Third, although we did not find effort expectancy and social influence to directly affect use intention, these two factors may still affect it indirectly via so-called crossover effects (Taylor & Todd, 1995). This is why their role should not be entirely ignored. For example, as hypothesised in the technology acceptance model (TAM) by Davis (1989), technologies that are perceived as easier to use are also typically perceived as more useful, suggesting a link between effort expectancy and performance expectancy. A similar link may also exist between effort expectancy and habit because use behaviour can be assumed to become habitual more easily in the case of technologies that are perceived as easy to use.

7 Limitations and Future Research

This study can be considered to have four main limitations. First, the study concentrated on only one particular type of digital wellness technology for promoting the physical activity among young elderly: physical activity logger applications. This obviously limits the generalisability of its findings in terms of other digital wellness technologies. Second, the research setting of the study does not fully correspond to the real-life market environment in which consumers make decisions on technology acceptance and use. For example, the participants were provided for free with both the application as well as the training and support for installing and using it. Without these, factors such as facilitating conditions and price value, which were omitted in the research model of the study, may also play an important part as antecedents of use intention and use behaviour. Third, the research model of the study concentrated only on use intention and not on actual use behaviour. Although the link between use intention and use behaviour is hypothesised in theories like the aforementioned TAM, UTAUT, and UTAUT2, future studies should also aim at empirically verifying it by incorporating the use behaviour construct into their research models and collecting data on actual use. This is already part of our future plans. In our future studies, when we are able to recruit more participants to our research program, we are also planning to increase our sample size, which will allow, for example, the examination of more complex interaction effects between the constructs of our research model.

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