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A FOLLOW-UP ON THE CHANGES IN THE USE INTENTION OF DIGITAL WELLNESS TECHNOLOGIES AND ITS ANTECEDENTS OVER TIME: THE USE OF PHYSICAL ACTIVITY LOGGER APPLICATIONS AMONG YOUNG ELDERLY IN FINLAND

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Abstract This study aims to further promote the understanding of the antecedents of the acceptance and use of digital wellness technologies among elderly people through a follow-up to our two prior studies, one which examines the potential longer-term temporal changes in the use intention of digital wellness technologies and its antecedents in the case of the young elderly segment and physical activity logger applications. We base this examination theoretically on UTAUT2 and empirically on survey data that is collected from 92 Finnish young elderly users of a physical activity logger application in three subsequent time points and analysed with partial least squares structural equation modelling (PLS-SEM). We find that the initial strong decline in the scores of the antecedent constructs and use intention becomes weaker as the construct scores stabilise over time, whereas especially the effects of performance expectancy and effort expectancy on use intention remain relatively unstable.

Keywords:
digital
wellness
technologies,
physical
activity
logger
applications,
young
elderly,
follow-up,
UTAUT2,
partial
least
squares

1 Introduction

Physical inactivity has become an increasingly prevalent problem among elderly people (Sun, Norman & While, 2013), thus raising a call for new and innovative ways to promote their levels of physical activity. One potential way to do 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., McGarrigle & Todd, 2020). In addition to elderly people in general, their potential has been highlighted especially in the more specific segment of young elderly, which consists of people aged approximately 60–75 years (e.g., Carlsson & Walden, 2016). However, there is a lack of prior studies that have examined the antecedents of the acceptance and use of digital wellness technologies among elderly people, particularly from a longitudinal perspective of how their use evolves after the initial acceptance. These kinds of longitudinal studies can be considered highly important in the context of digital wellness technologies because, as it is suggested in theories like the lived informatics model of personal informatics (Epstein, Ping, Fogarty & Munson, 2015), the use of these technologies, especially those aimed at self-tracking, is often characterised by “lapses” in their use. This suggests that the intention to use the technologies and its antecedents do not remain constant but change over time. However, in prior information systems (IS) literature, such temporal changes have not been studied from the perspective of technology acceptance and use.

The objective of this study is to address this gap in prior research by studying *how the use intention of digital wellness technologies and its antecedents among elderly people potentially change over time*. We examine this research question 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 keep track of their physical activities in everyday life as well as view different types of reports about them. As the theoretical foundation for conceptualising the antecedents of the intention to use physical activity logger applications and formulating the research model for examining the potential temporal changes in use intention and its antecedents, we use UTAUT2 by Venkatesh, Thong, and Xu (2012), which is one of the most comprehensive and established IS theories for explaining technology acceptance and use in consumer contexts, such as the one of this study. In turn, as the empirical data for the

examination, we use survey data that is collected from 92 Finnish young elderly users of a physical activity logger application in three subsequent time points and analysed with partial least squares structural equation modelling (PLS-SEM). The study was conducted as part of our broader DigitalWells research program, which focuses on young elderly in Finland and in which the participants are provided for free both a physical activity logger application to keep track of their daily physical activities as well as the training and support for setting up and using it. The study is a follow-up to our two prior studies (Makkonen, Kari & Frank, 2020, 2021), in which we initially proposed and tested our research model for explaining the acceptance and use of digital wellness technologies in the case of young elderly and physical activity logger applications as well as examined the potential changes in use intention and its antecedents between about four months and about 12 months of use. Here, this time span is extended to about 18 months, thus enabling the examination of even longer-term changes.

After this introductory section, we describe in more detail the research model and the research methodology of the study in Sections 2 and 3. This is followed by reporting of the research results in Section 4. The results are discussed in more detail in Section 5 before concluding the paper with a brief discussion about the limitations of the study and some potential paths of future research in Section 6.

2 Research Model

As already mentioned above, 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 IS contexts, including also the context of mobile health and fitness applications and devices (e.g., Yuan, Ma, Kanthawala & Peng, 2015; Duarte & Pinho, 2019; Talukder, Chiong, Bao & Malik, 2019; Dhiman, Arora, Dogra & Gupta, 2020; Beh, Ganesan, Iranmanesh & Foroughi, 2021) and the context of elderly users (e.g., Macedo, 2017). However, none of these prior studies have combined the two contexts by examining, for example, the acceptance and use of physical activity logger applications among young elderly, as it is done in this study. In UTAUT2, the *behavioural intention* (BI) to use a particular technology is

hypothesised to be positively affected by seven antecedents (Venkatesh et al., 2012): *performance expectancy* (PE – i.e., the degree to which using a technology will provide benefits to consumers in performing certain activities), *effort expectancy* (EE – i.e., the degree of ease associated with consumers' use of technology), *social influence* (SI – i.e., the extent to which consumers perceive that important others believe they should use a particular technology), *facilitating conditions* (FC – i.e., consumers' perceptions of the resources and support available to perform a behaviour), *hedonic motivation* (HM – i.e., the fun or pleasure derived from using a technology), *price value* (PV – i.e., the consumers' cognitive trade-off between the perceived benefits of the technology and the monetary cost for using it), and *habit* (HT – i.e., the extent to which people tend to perform behaviours automatically because of learning). In addition, UTAUT2 hypothesises three moderators for the effects of these seven antecedents on use intention: age, gender, and experience. However, due to the limited sample size of this study, these moderators are omitted from the research model. In addition, we omit two of the seven antecedents: facilitating conditions and price value. These were considered irrelevant in the present study because the application was free for all the participants and they all had the same resource requirements for taking part in the research program (e.g., owning a smartphone on which the application can be installed) as well as were given the same training and support for setting up and using the application, thus assumably resulting in very low variance in their perceptions of these issues. Finally, as in many studies on technology acceptance and use, the research model also concentrates on explaining only use intention and not actual *use behaviour* (UB). The final research model of the study, with the omitted constructs and effects presented as dashed, is illustrated in Figure 1.

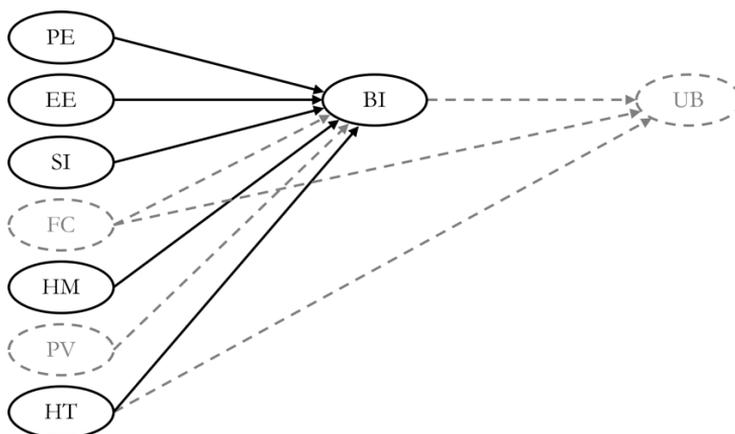


Figure 1: Research model (the dashed constructs and effects are omitted in this study)

3 Methodology

The data for the study was collected from the participants of our research program in three subsequent surveys. These were conducted in autumn 2019 after about four months of using the application, in summer 2020 after about 12 months of using the application, and in winter 2021 after about 18 months of using the application. In the remainder of this paper, these three time points, respectively, are referred to as T1, T2, and T3. The first survey was administered as a pen-and-paper survey in face-to-face group meetings with the participants, whereas the second and third survey were both administered as online surveys due to the ongoing COVID-19 pandemic. Because Finland has two official languages, the participants had the option to respond to the surveys in either Finnish or Swedish. In the surveys, each construct of the research model was measured reflectively by three indicators. All the indicators were adapted from the study by Venkatesh et al. (2012) and their wordings in English are reported in Table 1. The measurement scale was a seven-point Likert scale ranging from one (strongly disagree) to seven (strongly agree). Because we wanted to avoid forced responses, the participants also had the option not to respond to a particular item, which resulted in a missing value.

Table 1: Indicator wordings

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 limited sample size of this study, the collected data was analysed with variance-based structural equation modelling (VB-SEM), more specifically partial least squares structural equation modelling (PLS-SEM). As a statistical software for PLS-SEM, we used SmartPLS 3.3.3 by Ringle, Wende, and Becker (2015). We also followed carefully the previously published guidelines for conducting PLS-SEM in IS research given by Hair, Hollingsworth, Randolph, and Chong (2017). For example, in accordance with the given guidelines, we used mode A as the indicator weighting mode of the constructs, path weighting as the weighting scheme, +1 as the initial weights, and $< 10^{-7}$ as the stop criterion in model estimation, whereas the statistical significance of the model estimates was tested by using bootstrapping with 5,000 subsamples. As the threshold for statistical significance, we used $p < 0.05$. The potential missing values were handled by using mean replacement.

The estimated model consisted of three submodels, which were otherwise identical and formulated based on the research model illustrated in Figure 1, but which were estimated by using the data collected at T1, T2, and T3, respectively. The three submodels were also connected by so-called carry-over effects (cf. Roemer, 2016), which were used to examine how the scores of a specific construct at a previous time point (i.e., T1 or T2) affect the scores of that same construct at a subsequent time point (i.e., T2 or T3). After estimating the model and evaluating the reliability and validity of its three submodels at both construct and indicator levels, the potential changes in the estimated construct scores and effect sizes from T1 to T2 and from T2 to T3 were examined. This examination followed the procedure proposed by Roemer (2016) for evolution models with panel data (also referred to as model type A.1 in her paper). First, the statistical significance of the changes in the means of the estimated unstandardised construct scores from T1 to T2 and from T2 to T3 were tested by using the parametric Student's paired samples t-test. Its results were additionally confirmed by using the nonparametric Wilcoxon (1945) signed-rank test if the compared means were not found to be normally distributed as suggested by the Shapiro-Wilk (1965) test. Second, the estimated size of each effect at a previous time point (i.e., T1 or T2) was compared against the 95% bias-corrected and accelerated (BCa) confidence interval (cf. Hair, Hult, Ringle & Sarstedt, 2017) of the estimated size of that same effect at a subsequent time point (i.e., T2 or T3). If the estimate at the previous time point did not fall within the confidence interval of the estimate at the subsequent time point, then the change in the effect size could be considered statistically significant.

4 Results

In total, 115 participants provided valid responses to the survey at T1, of which 99 participants did so also at T2 (a drop-out rate of 13.9%), and of which 92 participants did so also at T3 (a drop-out rate of 7.1%). The descriptive statistics of these three samples in terms of the gender, age, and response language of the participants as well as a subjective assessment of their level of physical activity are reported in Table 2. As can be seen, the drop-outs did not result in any considerable changes in the sample profiles. As the sample for this particular study, we used the last-mentioned sample of 92 participants who had provided valid responses to the survey at all the three time points. Of them, about two-thirds were women and over nine out of ten

assessed their level of physical activity as moderate or higher. Their age ranged from 49 to 79 years, with a mean of 69.1 years and a standard deviation of 4.7 years. Although some of the participants were slightly younger or older than our target young elderly segment consisting of people aged approximately 60–75 years, we decided not to omit these people from the study due to our limited sample size.

Table 2: Sample statistics

	T1 (N = 115)		T2 (N = 99)		T3 (N = 92)	
	N	%	N	%	N	%
Gender						
Man	43	37.4	34	34.3	32	34.8
Woman	72	62.6	65	65.7	60	65.2
Age						
Under 60 years	3	2.6	2	2.0	2	2.2
60–64 years	11	9.6	10	10.1	8	8.7
65–69 years	44	38.3	39	39.4	38	41.3
70–74 years	39	33.9	35	35.4	32	34.8
75 years or over	18	15.7	13	13.1	12	13.0
Language						
Finnish	69	60.0	63	63.6	60	65.2
Swedish	46	40.0	36	36.4	32	34.8
Level of physical activity						
Very high	1	0.9	1	1.0	1	1.1
High	18	15.7	16	16.2	15	16.3
Moderate	84	73.0	73	73.7	68	73.9
Low	4	3.5	3	3.0	3	3.3
Very low	8	7.0	6	6.1	5	5.4
Totally passive	0	0.0	0	0.0	0	0.0

4.1 Model Estimation

The estimation results of the three submodels in terms of the standardised size and statistical significance of the effects of the antecedent constructs on use intention at T1, T2, and T3 are reported in Table 3. As the reported values show, at all the three time points, the effects of hedonic motivation and habit were found to be positive and statistically significant, whereas the effect of social influence was found to be statistically not significant. In contrast, performance expectancy was found to have a positive and statistically significant effect at T1 and T3, but a statistically not significant effect at T2, whereas effort expectancy was found to have a positive and statistically significant effect at T2, but a statistically not significant effect at T1 and

T3. In terms of explanatory power, the proportion of explained variance (R^2) in use intention was 72.7% at T1, 77.3% at T2 and 83.2% at T3.

Table 3: Effects on use intention (*) = $p < 0.001$, ** = $p < 0.01$, * = $p < 0.05$)**

	T1		T2		T3	
	Size	95% CI	Size	95% CI	Size	95% CI
PE → BI	0.348**	[0.140, 0.567]	0.091	[-0.129, 0.324]	0.337**	[0.143, 0.565]
EE → BI	0.064	[-0.092, 0.225]	0.324***	[0.177, 0.493]	0.077	[-0.083, 0.278]
SI → BI	0.025	[-0.109, 0.146]	0.091	[-0.041, 0.207]	-0.047	[-0.202, 0.078]
HM → BI	0.247**	[0.069, 0.420]	0.243**	[0.085, 0.399]	0.267*	[0.019, 0.519]
HT → BI	0.308**	[0.102, 0.509]	0.272*	[0.069, 0.497]	0.227**	[0.060, 0.382]

Table 4: Carry-over effects (*) = $p < 0.001$, ** = $p < 0.01$, * = $p < 0.05$)**

	T1 → T2		T2 → T3	
	Size	R^2 by T1 at T2	Size	R^2 by T2 at T3
PE → PE	0.453***	0.205	0.707***	0.500
EE → EE	0.295*	0.087	0.624***	0.389
SI → SI	0.534***	0.285	0.600***	0.360
HM → HM	0.466***	0.217	0.801***	0.641
HT → HT	0.466***	0.217	0.763***	0.582
BI → BI	0.107*	0.045	0.146	0.110

In turn, Table 4 reports the standardised size and statistical significance of the carry-over effects between the constructs of the three submodels as well as the proportion of explained variance (R^2) in the scores of a specific construct at a subsequent time point by the scores of that same construct at a previous time point. As the reported values show, all the carry-over effects except for the one concerning use intention between T2 and T3 were found to be statistically significant. All the carry-over effects also seemed to be considerably stronger between T2 and T3 in comparison to T1 and T2, meaning that the construct scores provided by the participants became more stable over time. The only slight exceptions to this were the carry-over effects concerning social influence and use intention, which remained approximately equally strong between T1 and T2 as well as T2 and T3.

4.2 Construct Reliability and Validity

Table 5: Construct statistics

		CR	AVE	PE	EE	SI	HM	HT	BI
PE	T1	0.908	0.766	0.875					
	T2	0.898	0.746	0.864					
	T3	0.904	0.759	0.871					
EE	T1	0.876	0.703	0.464	0.838				
	T2	0.879	0.707	0.586	0.841				
	T3	0.940	0.840	0.572	0.917				
SI	T1	0.930	0.816	0.485	0.297	0.903			
	T2	0.861	0.675	0.513	0.452	0.822			
	T3	0.902	0.754	0.635	0.369	0.868			
HM	T1	0.932	0.820	0.677	0.472	0.533	0.906		
	T2	0.903	0.756	0.742	0.520	0.391	0.869		
	T3	0.949	0.860	0.830	0.674	0.595	0.927		
HT	T1	0.815	0.597	0.698	0.474	0.478	0.667	0.773	
	T2	0.875	0.700	0.754	0.529	0.484	0.642	0.837	
	T3	0.870	0.691	0.793	0.564	0.510	0.729	0.831	
BI	T1	0.891	0.733	0.772	0.495	0.491	0.732	0.758	0.856
	T2	0.913	0.777	0.759	0.706	0.538	0.727	0.755	0.881
	T3	0.895	0.741	0.850	0.653	0.522	0.843	0.810	0.861

Construct reliabilities were evaluated by examining the composite reliability (CR) of each construct (Fornell & Larcker, 1981), which is commonly expected to be greater than or equal to 0.7 (Nunnally & Bernstein, 1994). The CR of each construct at T1, T2, and T3 is reported in the first column of Table 5, showing that all the constructs at all the three time points clearly met this criterion. In turn, construct validities were evaluated by examining the convergent and discriminant validities of the constructs by using two criteria based on the average variance extracted (AVE) of each construct (Fornell & Larcker, 1981). In order to exhibit satisfactory convergent validity, the first criterion requires that each construct should have an AVE of at least 0.5. The AVE of each construct at T1, T2, and T3 is reported in the second column of Table 5, showing that all the constructs at all the three time points met also this criterion. In turn, in order to exhibit satisfactory discriminant validity, the second criterion requires that each construct should have a square root of AVE greater than or equal to its absolute correlation with the other model constructs. The square root of AVE of each construct at T1, T2, and T3 (on-diagonal cells) and the correlations between the constructs at T1, T2, and T3 (off-diagonal cells) are

reported in the remaining columns of Table 5, showing that also this criterion was met by all the constructs at all the three time points.

4.3 Indicator Reliability and Validity

Table 6: Indicator statistics (***) = all loadings have $p < 0.001$)

	T1				T2				T3			
	Mean	SD	NA	λ^{***}	Mean	SD	NA	λ^{***}	Mean	SD	NA	λ^{***}
PE1	5.682	1.474	4.3%	0.863	5.473	1.515	1.1%	0.855	5.045	1.685	3.3%	0.896
PE2	5.284	1.494	12.0%	0.892	4.722	1.696	2.2%	0.833	4.943	1.564	4.3%	0.824
PE3	5.216	1.572	4.3%	0.870	4.945	1.656	1.1%	0.902	4.878	1.648	2.2%	0.892
EE1	6.330	1.155	1.1%	0.832	5.811	1.564	2.2%	0.851	5.978	1.382	1.1%	0.934
EE2	6.143	1.179	1.1%	0.882	5.934	1.315	1.1%	0.809	5.826	1.573	0.0%	0.938
EE3	5.747	1.495	1.1%	0.799	5.167	1.691	2.2%	0.862	5.477	1.576	4.3%	0.876
SI1	4.264	2.130	21.7%	0.916	4.090	1.949	15.2%	0.860	3.975	2.124	14.1%	0.903
SI2	4.603	2.110	26.1%	0.925	3.939	1.990	10.9%	0.770	3.695	2.141	10.9%	0.880
SI3	5.219	1.797	20.7%	0.868	4.538	1.855	13.0%	0.832	4.679	2.042	15.2%	0.820
HM1	5.739	1.255	4.3%	0.932	5.352	1.456	1.1%	0.859	5.011	1.742	1.1%	0.945
HM2	5.906	1.076	7.6%	0.894	5.270	1.643	3.3%	0.894	5.185	1.630	0.0%	0.903
HM3	5.141	1.536	7.6%	0.891	4.571	1.634	1.1%	0.854	4.611	1.733	2.2%	0.934
HT1	6.135	1.333	3.3%	0.758	5.833	1.448	2.2%	0.841	5.231	1.820	1.1%	0.840
HT2	4.241	1.935	9.8%	0.712	3.956	1.914	1.1%	0.839	3.899	1.995	3.3%	0.819
HT3	5.136	1.717	4.3%	0.842	4.615	1.855	1.1%	0.831	4.333	1.818	2.2%	0.834
BI1	5.869	1.495	8.7%	0.858	5.831	1.487	3.3%	0.904	5.639	1.551	9.8%	0.841
BI2	5.595	1.262	8.7%	0.808	4.822	1.680	2.2%	0.873	4.890	1.722	1.1%	0.864
BI3	5.841	1.437	4.3%	0.899	5.523	1.470	4.3%	0.867	5.379	1.713	5.4%	0.877

Indicator reliabilities and validities were evaluated by using the standardised loading (λ) of each indicator, which are reported at T1, T2, and T3 in Table 6 together with the mean and standard deviation (SD) of the indicator scores as well as the percentage of missing values (NA). In the typical case where each indicator loads on only one construct, its standardised loading is commonly expected to be statistically significant and greater than or equal to 0.707 (Fornell & Larcker, 1981). As the reported values show, all the indicators at all the three time points met this criterion.

4.4 Changes in Construct Scores

Table 7: Construct scores and the changes in construct scores

	T1		T2		T3		$\Delta T1 \rightarrow T2$		$\Delta T2 \rightarrow T3$	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD
PE	5.396	1.279	5.077	1.387	4.957	1.405	-0.320	1.398	-0.120	1.069
EE	6.082	1.056	5.670	1.260	5.770	1.367	-0.412	1.385	0.101	1.143
SI	4.726	1.584	4.219	1.475	4.120	1.698	-0.507	1.479	-0.099	1.434
HM	5.634	1.111	5.077	1.356	4.931	1.570	-0.557	1.292	-0.146	0.946
HT	5.265	1.229	4.925	1.417	4.531	1.538	-0.340	1.378	-0.394	1.025
BI	5.754	1.141	5.411	1.336	5.317	1.389	-0.343	1.346	-0.094	0.961

Table 8: Testing of the changes in construct scores

	$\Delta T1 \rightarrow T2$					$\Delta T2 \rightarrow T3$				
	Student's t-test			Wilcoxon test		Student's t-test			Wilcoxon test	
	t	df	p	z	p	t	df	p	z	p
PE	-2.192	91	0.031	-1.429	0.153	-1.078	91	0.284	-1.150	0.250
EE	-2.854	91	0.005	-2.746	0.006	0.844	91	0.401	-1.215	0.224
SI	-3.287	91	0.001	-3.754	< 0.001	-0.661	91	0.510	-0.289	0.773
HM	-4.132	91	< 0.001	-4.188	< 0.001	-1.479	91	0.143	-1.335	0.182
HT	-2.366	91	0.020	-2.481	0.013	-3.684	91	< 0.001	-3.559	< 0.001
BI	-2.446	91	0.016	-2.924	0.003	-0.940	91	0.350	-0.537	0.591

In terms of the changes in construct scores, Table 7 reports the means and standard deviations (SD) of the estimated unstandardised construct scores at T1, T2, and T3 as well as the means and standard deviations (SD) of the changes in them from T1 to T2 and from T2 to T3. As can be seen, the participants had relatively high scores in the case of all the constructs at all the three time points, but the scores seemed to decline over time, more drastically from T1 to T2 and less drastically from T2 to T3. The statistical significance of these changes was tested by using both parametric and nonparametric testing because most of the compared construct mean scores were not found to be normally distributed. The results of these tests are reported in Table 8, showing that from T1 to T2, the changes in the construct mean scores were found to be statistically significant in the case of all the antecedent constructs except potentially for performance expectancy, in the case of which the statistical significance of the change suggested by parametric testing could not be confirmed

by nonparametric testing. In contrast, from T2 to T3, the changes in the construct mean scores were found to be statistically significant only in the case of habit.

4.5 Changes in Effect Sizes

In terms of the changes in effect sizes, Table 3 additionally reports the 95% confidence interval (CI) of the estimated size of each effect at T1, T2, and T3. As can be seen, the estimated size of the effects of performance expectancy and effort expectancy at T1 and T2, respectively, did not fall within the 95% CI of the estimated size of the same effects at T2 and T3, respectively, thus suggesting that the changes in the size of these effects from T1 to T2 and from T2 to T3 were statistically significant. More specifically, the effect of performance expectancy seemed to become weaker from T1 to T2 and stronger from T2 to T3, whereas the effect of effort expectancy seemed to become stronger from T1 to T2 and weaker from T2 to T3. In addition, the estimated size of the effect of social influence at T2 did not fall within the 95% CI of the estimated size of the same effect at T3, but this effect remained statistically not significant at both these two time points.

5 Discussion and Conclusions

In this study, we examined the potential longer-term temporal changes in the use intention of digital wellness technologies and its antecedents in the case of the young elderly segment and physical activity logger applications. In comparison to our two prior studies (Makkonen et al., 2020, 2021), we made three main findings. First, we found that our research model continued to perform very well in explaining use intention also after about 18 months of using the application by being able to explain about 83% of its variance at T3 as well as having acceptable reliability and validity at both construct and indicator levels. Thus, it seems to be well suited also for longitudinal study settings in which the time span extends well beyond one year. Second, we found that the strong decline in the scores of the antecedent constructs and use intention from T1 to T2 became weaker in the case of most of the constructs from T2 to T3, which was also supported by the finding concerning the stabilisation of the construct scores over time. The only exception to this was habit, the scores of which continued to decline about as strongly between T2 and T3 as between T1 and T2, although its scores also became more stable over time. This initially strong but then increasingly weaker decline in the construct scores is most likely explained

by a novelty effect that causes a particular digital wellness technology to be first perceived very favourably by its potential users but these perceptions to converge towards realism as the use progresses, first more quickly, as also the hype concerning the technology is higher, but then more slowly. Third, we found that the effects of social influence, hedonic motivation, and habit on use intention continued to remain very stable between T2 and T3, as they did also between T1 and T2, whereas more instability could be observed in the effects of performance expectancy and effort expectancy. That is, whereas the effect of performance expectancy become weaker and the effect of effort expectancy stronger from T1 to T2, these changes were now reversed, with the effect of performance expectancy once again becoming stronger and the effect of effort expectancy weaker. What is actually causing this instability, as well as whether it is driven more by internal changes in the users themselves or external changes in their environment, requires more in-depth examinations. However, all in all, the aforementioned temporal changes in both the effects of the antecedent constructs on use intention and the scores of the antecedent constructs themselves would seem to provide some much-needed theoretical explanations for the “lapses” in the use of personal informatics or self-tracking technologies, such as physical activity logger applications, which have been suggested in theories like the lived informatics model of personal informatics (Epstein et al., 2015). In turn, from a more practical perspective, the findings of the study highlight the need for the providers of various digital wellness technology products and services to actively adapt their offerings to the aforementioned temporal changes as well as to continuously promote the novelty of their offerings through approaches like gamification (e.g., Kari, Piippo, Frank, Makkonen & Moilanen, 2016) and exergaming (e.g., Kari, 2014; Kari & Makkonen, 2014) in order to prevent the perceptions of the users from becoming less favourable as the initial novelty effect fades out.

6 Limitations and Future Research

Like our two prior studies, this study can be considered to have three main limitations. First, the study focused on the specific case of physical activity logger applications and the Finnish young elderly segment, which is why future studies are called for to examine the generalisability of its findings to other types of digital wellness technologies and to the elderly population in general. 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 both the application as well as the training and support for setting up and using it, without which factors like facilitating conditions and price value may also have played an important role as antecedents of use intention. Third, there were some participants who left the research program already before T1 or between T1 and T2 or T2 and T3, and, thus, had to be omitted from the study. Some of them may have been individuals who would have reported very low scores in terms of use intention and its antecedents and whose omission, consequently, may have introduced some bias in the data. In future studies, we aim to address these aforementioned limitations and to augment the preliminary results of this study by refining our research model as well as collecting data from more participants and over a longer period of time as our research program progresses.

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