Author(s): Makkonen, Markus; Kari, Tuomas; Frank, Lauri; Moilanen, Panu

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Adoption and Adoption Interests of Self-Tracking Technologies: *Single and Multiple Technology Perspectives*

Markus Makkonen

University of Jyvaskyla, Finland
markus.v.makkonen@jyu.fi

Tuomas Kari

University of Jyvaskyla, Finland
tuomas.t.kari@jyu.fi

Lauri Frank

University of Jyvaskyla, Finland
lauri.frank@jyu.fi

Panu Moilanen

University of Jyvaskyla, Finland
panu.moilanen@jyu.fi

Abstract

During the past few decades, different forms of technology based self-tracking have become increasingly common but received little attention in academic research. In this study, we aim to address this gap by examining the adoption and adoption interests of four different self-tracking technologies: exercise, activity, sleep, and nutrition tracking. The examination is conducted from both single and multiple technology perspectives and by concentrating particularly on the potential gender and age dependencies in the adoption rates and adoption patterns of the technologies. By analysing the responses collected from 824 consumers through an online survey, the results of the study are able to reveal that although the adoption rates of all the four self-tracking technologies still remain relatively low, there is considerable interest towards the adoption of all of them. In addition, based on the differences in their adoption patterns, four distinct consumer segments can be identified.

Keywords: Self-Tracking Technologies, Adoption, Adoption Interests, Single Technology Perspective, Multiple Technology Perspective, Survey

1 Introduction

During the past few decades, the developments in information and communication technology (ICT) have vastly expanded the range of variables that we are able to track in ourselves and made different forms of technology based self-tracking increasingly common. For example, many of us wear an activity tracker on one's wrist to keep in track of the daily step count or strap a heart rate monitor around one's chest to get more detailed data on the effects of exercising. Respectively, it is common for many to keep a diary on their daily intake of food and drinks or track their nightly sleep with sensors placed onto one's body or into one's bed. At the same time, self-tracking has also become major business. For example, the market of health self-monitoring technologies has been expected to grow from $3.2 billion in 2014 to $18.8 billion by 2019 (BCC Research, 2015) and the market of smart wearables for sports and fitness from $3.5 billion in 2014 to $14.9 billion by 2021 (Wintergreen Research, 2015).

In spite of all this, self-tracking has so far received relatively little attention in academic research, with most prior studies being only opinion or commentary type of papers introducing the phenomena of self-tracking (e.g., Smarr 2012, Lupton, 2013b; Swan, 2013) or considering its implications on areas like health care (e.g., Swan, 2009, 2012; Lupton, 2013a). In contrast, there have been few actual empirical studies concentrating, for example, on the adoption of self-tracking technologies in an attempt to answer such fundamental questions as how widely these technologies are actually used and by whom as well as what kind of factors drive or deter their adoption. In addition, the few prior studies that have been made on the topic, have all examined the phenomenon from a relatively narrow single technology perspective, such as the adoption of heart rate monitors (Makkonen et al., 2012a) or pedometers and route trackers (Makkonen et al., 2012b), whereas none of them have taken a wider multiple technology perspective concentrating on the simultaneous adoption of not only one, but several different self-tracking technologies. Such a wider perspective can be considered beneficial especially because it enables us to study also the potential dependencies in the adoption patterns of different technologies. For example, some technologies may act as "gatekeeper" technologies whose adoption is a necessary prerequisite for the adoption of other technologies. Similarly, there may also be technologies whose adoption hinders or totally blocks the adoption of others. Of course, also many other kinds of dependencies are possible, but observable only through the aforementioned multiple rather than single technology perspective.

In this study, we aim to address this gap in prior research by examining the adoption of four different self-tracking technologies from both single and multiple technology perspectives: exercise tracking, activity tracking, sleep tracking, and nutrition tracking. These four technologies can be seen as covering the most typical cases in which individuals today track themselves. We concentrate on adoption mainly from a macro-level diffusion perspective by examining the adoption rates and adoption patterns of the aforementioned technologies as well as their potential dependencies on gender and age, which have been found affecting technology adoption or acceptance in theories like the unified theory of acceptance and use of technology (UTAUT) by Venkatesh et al. (2003) as well as its successor UTAUT2 by Venkatesh, Thong and Xu (2012). However, our study differs from many adoption studies in terms of operationalising adoption not as a simple dichotomous variable, but taking into account also adoption interests. These adoption interests can be assumed to correlate with adoption intentions, which have been found as crucial antecedents of actual adoption in the aforementioned UTAUT and

UTAUT2 as well as also in their predecessor the technology acceptance model (TAM) by Davis (1989) as well as Davis, Bagozzi and Warshaw (1989).

This paper consists of six sections. After this introductory section, we briefly discuss the concepts of self-tracking and self-tracking technologies in Section 2. Sections 3 and 4 report the methodology and results of the study. The results are discussed in more detail in Section 5, which also uses them to draw implications for both theory and practice. Finally, Section 6 considers the limitations of the study and potential paths of future research.

2 Self-Tracking and Self-Tracking Technologies

In this study, with *self-tracking*, we refer to the activity of tracking one's physiological or psychological properties, behaviour, thoughts, or any other relevant aspect of oneself independent of the tracking context. However, there are also several other terms which are commonly used to refer to similar activities, such as quantified self, personal informatics, personal analytics, lifelogging, self-monitoring, and self-surveillance (Choe et al., 2014). Some of these can be considered synonyms to self-tracking, whereas others are more commonly used in specific tracking contexts.

Quantified self is nowadays one of the most commonly used of the aforementioned terms. Originally coined by Gary Wolf and Kevin Kelly (Wolf, 2009, 2010), it refers both to a community of people interested in self-tracking (Quantified Self Labs, 2016) as well as to self-tracking activity itself. In quantified self, there is typically a strong proactive stance towards not only obtaining data on oneself but also reflecting it and acting on it in a spirit of self-experimentation (Swan, 2013). Closely related concepts emphasising not only the data collection but also the data reflection aspect are *personal informatics* (Li, Dey & Forlizzi, 2010) and *personal analytics* (Wolfram, 2012). *Lifelogging*, in turn, refers to the activity of recording aspects of one's life in a digital form (Doherty et al., 2011) in an attempt to create a sort of a digital memory (Bell & Gemmel, 2009). Such activity may be passive, in which one only collects and stores the by-products of one's life, or active, in which one surrounds oneself with self-tracking technologies to create as rich a picture of one's life as possible (O'Hara, Tuffield & Shadbolt, 2008). A division can also be made between total capture and situation-specific capture, of which the former aims at a complete record of one's life, whereas the latter limits itself to specific situations (Sellen & Whittaker, 2010). However, lifelogging typically concentrates more on the data collection than on the data analysis aspect of self-tracking. Finally, *self-monitoring* is more commonly used in health care or mobile health (m-health) contexts (e.g., Lupton, 2013a). This also applies to self-surveillance, although it is typically used in more critical discussions about self-tracking (e.g., Lupton, 2012).

Respectively, with *self-tracking technologies*, we refer in this study to the technological solutions that enable self-tracking activities, such as the devices used in collecting the data on ourselves through sensors and other methods as well as the services used in storing and analysing this data. The variables tracked through these technologies can be categorised, for example, into diet, physical activities, psychological states and traits, mental and cognitive states and traits, environmental variables, situational variables, and social variables (Swan, 2013) or alternatively into exercise, work, mind, sleep, and nutrition (Arina, Sovijärvi & Halmetoja, 2016). This latter categorisation acts as a basis for the categorisation used in this study, in which we separate self-tracking technologies into exercise, activity, sleep, and nutrition tracking technologies.

3 Methodology

The data for this study comes from a self-administered online survey commissioned by the Finnish insurance company LähiTapiola and conducted by the market and opinion research company YouGov Finland between 9–11 February 2015 by using their panel of over 20,000 Finnish consumers. In the survey questionnaire, the respondents were first asked about their background information, such as gender, age, household income, and socioeconomic status. This was followed by questions on various health and well-being related topics, such as their insurances, health and well-being related spending, and opinions on public and private health service providers. Finally, the respondents were also asked about their adoption of exercise, activity, sleep, and nutrition tracking, and the responses to this question were used as the data for this study alongside with the information on gender and age. The question was a multiple-choice question consisting of two sub-questions in which the respondents reported (A) which of the four self-service technologies they had already adopted (i.e., were already using for self-tracking) and (B) which of the four self-service technologies they were interested in adopting (i.e., were interested in using for self-tracking). The exact wording of the question, translated from Finnish to English, is presented in Appendix A. Based on their answers to the question, the respondents were categorised as (1) adopters of a specific self-tracking technology if they had selected it in sub-question A, (2) being interested in adopting a specific self-tracking technology if they had not selected it in sub-question A but had selected it in sub-question B, and (3) non-adopters of a specific self-tracking technology if they had selected it in neither of the sub-questions. In addition, the respondents also had the option to indicate that they did not want to disclose their adoption or adoption interests, in which case they were excluded from further analyses.

This collected and categorised data was then analysed with the SPSS Statistics version 22 software in two phases. In the first phase, we concentrated on single technology perspective and conducted simple frequency analyses in order to examine the adoption and interest rates of each self-tracking technology. We also used contingency tables, the Pearson's residuals (or adjusted standardised residuals), and the Pearson's χ^2 tests to examine the dependencies of these rates on gender as well as one-way analysis of variance (1-ANOVA) and post-hoc multiple comparisons based on the Tukey's test to examine their dependencies on age. In the second phase, we concentrated on multiple technology perspective and conducted a latent class analysis with the Mplus version 7.11 software in order to examine whether the respondents could be categorised into two or more latent classes based on their adoption and adoption interest. The number of the latent classes was determined without any *a priori* assumptions in an explorative manner, meaning that we begun with a two-class model and incrementally increased the number of classes, each time testing whether the fit of the k-1 class model was as good or better than the fit of the k class model to the data (k being the number of classes). As a test for this, we used the three likelihood ratio tests implemented in Mplus, which are the Vuong-Lo-Mendell-Rubin likelihood ratio test (Vuong, 1989), the Lo-

Mendell-Rubin adjusted likelihood ratio test (Lo, Mendell & Rubin, 2001), and the parametric bootstrapped likelihood ratio test (McLachlan & Peel, 2000). In addition, we also used the information provided by Mplus on the most likely latent class membership of the respondents to conduct analyses on the potential dependencies of latent class membership on gender and age in a similar manner than in the first phase.

4 Results

The conducted online survey was responded by a total of 1,003 adult Finnish consumers. Of them, however, 179 had to be excluded as they had not disclosed their adoption and adoption interests, resulting in a sample of 824 respondents to be used in the actual analyses. Descriptive statistics of the sample before and after the exclusion are reported in Table 1. As can be seen, the exclusion did not seem to result in any serious distortions in terms of gender, age, income, and socioeconomic status of the respondents. Also when compared to the gender and age distributions of the adult Finnish population in 2015 (Statistics Finland, 2016), which are also reported in Table 1, the final sample can be considered to represent reasonably well the adult Finnish consumers. For example, the age of the respondents ranged from 18 to 81 years, with the mean age being 46.9 years (SD = 14.8 years).

	N = 1,003		N = 824		Finland
	N	%	N	%	%
Gender					
Male	476	47.5	382	46.4	48.8
Female	527	52.5	442	53.6	51.2
Age					
18–29 years	163	16.3	140	17.0	18.3
30–39 years	163	16.3	140	17.0	15.9
40–49 years	176	17.5	140	17.0	15.1
50–59 years	261	26.0	212	25.7	16.8
60– years	240	23.9	192	23.3	33.9
Household income					
–26,999 €	242	24.1	204	24.8	
27,000–53,999 €	290	28.9	244	29.6	
54,000–80,999 €	196	19.5	158	19.2	
81,000–107,999 €	70	7.0	60	7.3	
108,000– €	35	3.5	32	3.9	
No response	170	16.9	126	15.3	
Socioeconomic status					
Working	613	61.1	510	61.9	
Student	69	6.9	60	7.3	
Pensioner	217	21.6	168	20.4	
Other	90	9.0	75	9.1	
No response	14	1.4	11	1.3	

Table 1: Sample statistics before (N = 1,003) and after (N = 824) the exclusion

4.1 Results from Single Technology Perspective

The absolute number and the relative percentage of respondents who had not yet adopted (and were not interested in adopting), who were interested in adopting, and who had already adopted a specific self-tracking technology are reported in Table 2. As can be seen, exercise tracking was by far the most commonly adopted self-tracking technology among the respondents with an adoption rate of 22.6 %, followed by activity tracking with an adoption rate of 13.6 %, sleep tracking with an adoption rate of 5.2 %, and finally nutrition tracking with an adoption rate of 3.4 %. Respectively, the self-tracking technology that clearly arouse most interest among the respondents was sleep tracking with an interest rate of 37.7 %, followed by activity tracking with an interest rate of 30.1 %, nutrition tracking with an interest rate of 28.4 %, and finally exercise tracking with an interest rate of 19.9 %.

		N	%
Exercise tracking	Not adopted	474	57.5
	Interested	164	19.9
	Adopted	186	22.6
Activity tracking	Not adopted	464	56.3
	Interested	248	30.1
	Adopted	112	13.6
Sleep tracking	Not adopted	470	57.0
	Interested	311	37.7
	Adopted	43	5.2
Nutrition tracking	Not adopted	562	68.2
	Interested	234	28.4
	Adopted	28	3.4

Table 2: Numbers and percentages of non-adopters, interested, and adopters

Table 3 reports the percentage of non-adopters, adopters, and those interested in adopting a specific self-tracking technology separately for men and women, whereas the results of the Pearson's X^2 tests that were used to examine the statistical significance of the potential differences in the percentages are reported in Table 4. As can be seen, the tests supported the null hypothesis of no difference in the case of exercise and sleep tracking but rejected it in the case of activity and nutrition tracking, thus suggesting that the adoption and adoption interests of these two self-tracking technologies were dependent on gender. To investigate these dependencies in more detail, Table 3 reports also the Pearson's residuals, which can be used to examine the statistical significance of each potential difference individually. As can be seen, statistically significant differences were found only in the interest rates of activity and nutrition tracking, which suggested women being more interested in both of these two self-tracking technologies. Although the same seemed to apply also to exercise and sleep tracking, these differences were not statistically significant. In turn, men seemed to have somewhat higher adoption rates of exercise, sleep, and nutrition tracking than women and women a somewhat higher adoption rate of activity tracking than men, but none of these differences were statistically significant.

		Men		Women	
		%	Residual	%	Residual
Exercise tracking	Not adopted	58.4	0.460	56.8	-0.460
	Interested	17.0	-1.930	22.4	1.930
	Adopted	24.6	1.299	20.8	-1.299
Activity tracking	Not adopted	63.1	3.647***	50.5	-3.647***
	Interested	24.6	-3.194**	34.8	3.194**
	Adopted	12.3	-1.003	14.7	1.003
Sleep tracking	Not adopted	58.9	1.004	55.4	-1.004
	Interested	34.6	-1.755	40.5	1.755
	Adopted	6.5	1.591	4.1	-1.591
Nutrition tracking	Not adopted	72.8	2.619**	64.3	-2.619**
	Interested	23.3	-3.018**	32.8	3.018**
	Adopted	3.9	0.779	2.9	-0.779

Table 3: Percentages of adopters, interested, and non-adopters in terms of gender

Dependency	X^2	df	p
Gender x exercise tracking	4.379	2	0.112
Gender x activity tracking	13.812	2	0.001
Gender x sleep tracking	4.750	2	0.093
Gender x nutrition tracking	9.289	2	0.010

Table 4: Results of the Pearson's X^2 difference tests

Table 5 reports the mean age of the non-adopters, adopters, and those interested in adopting a specific self-tracking technology, whereas the results of the 1-ANOVA tests that were used to examine the statistical significance of the potential differences in the mean ages are reported in Table 6. As can be seen, in the case of all the four self-tracking technologies, the test rejected the null hypothesis of no difference, thus suggesting that their adoption and adoption interests were dependent on age. However, it must be noted that in most of the examined groups, the normality assumption of ANOVA was not met when it was investigated by using the Kolmogorov-Smirnov test. Although this is likely to result in some underestimations of the p values, these underestimations are likely be quite insignificant because prior studies have found ANOVA to be very robust against non-normality (e.g., Schmider et al., 2010). In contrast, the homoscedasticity assumption of ANOVA was met in all the examined groups when tested with the Levene's test. To investigate the dependencies in more detail, Table 5 reports also the results of the Tukey's tests, which can be used to examine the statistical significance of each potential difference individually. As can be seen, in the case of all the four self-tracking technologies, the mean age of the non-adopters was found to be about 4–6 years higher in comparison to adopters and those interested in adoption, and this difference was found to be statistically significant in all cases except for nutrition tracking. In contrast, in the case of any of the four self-tracking technologies, no statistically significant differences were found between adopters and those interested in adoption, although the adopters were found to be slightly younger in comparison to those interested in adoption in all cases except for activity tracking.

		Mean (years)	SD (years)	Mean difference (years)		
				Not adopted	Interested	Adopted
Exercise tracking	Not adopted	49.1	14.8	–	4.9***	5.3***
	Interested	44.1	13.8	-4.9***	–	0.4
	Adopted	43.8	14.6	-5.3***	-0.4	–
Activity tracking	Not adopted	49.1	14.9	–	5.2***	4.5**
	Interested	43.9	14.0	-5.2***	–	-0.7
	Adopted	44.6	14.8	-4.5**	0.7	–
Sleep tracking	Not adopted	49.0	14.7	–	4.6***	6.2*
	Interested	44.3	14.5	-4.6***	–	1.6
	Adopted	42.7	13.4	-6.2*	-1.6	–
Nutrition tracking	Not adopted	48.2	14.9	–	3.9**	5.0
	Interested	44.3	13.9	-3.9**	–	1.1
	Adopted	43.1	15.5	-5.0	-1.1	–

Table 5: Mean ages of non-adopters, interested, and adopters

Dependency	F	df_1	df_2	p
Age x exercise tracking	12.374	2	821	< 0.001
Age x activity tracking	11.858	2	821	< 0.001
Age x sleep tracking	11.242	2	821	< 0.001
Age x nutrition tracking	6.802	2	821	0.001

Table 6: Results of the 1-ANOVA tests

4.2 Results from Multiple Technology Perspective

Table 7 reports the results of the Vuong-Lo-Mendell-Rubin likelihood ratio test (VLMR), the Lo-Mendell-Rubin adjusted likelihood ratio test (LMR), and the parametric bootstrapped likelihood ratio test (BLRT), which were used to test the null hypothesis of the fit of the k-1 class model being as good or better than the fit of the k class model to the data (k being the number of classes). As we can see, all the tests started to support the null hypothesis when k = 5, thus suggesting that four latent classes were sufficient for our estimated model.

k-1 vs. k latent classes	p of VLMR	p of LMR	p of BLRT
1 vs. 2 latent classes	< 0.001	< 0.001	< 0.001
2 vs. 3 latent classes	0.001	0.001	< 0.001
3 vs. 4 latent classes	0.001	0.001	< 0.001
4 vs. 5 latent classes	0.253	0.259	0.286

Table 7: Results of the likelihood ratio tests

Table 8 reports the model estimation results in a probability scale. The probabilities are conditional probabilities indicating how likely a member of a particular latent class is to not have adopted (and not being interested in adopting), be interested in adopting, or have already adopted a specific self-tracking technology. For example, we can see that the members of the first latent class are almost certain to have adopted activity and exercise tracking and also quite likely to have adopted sleep and nutrition tracking or at least being interested in adopting them. In contrast, the members of the second latent class are quite likely to have adopted exercise and activity tracking but unlikely to have adopted sleep and nutrition tracking. However, they are quite likely to be interested in adopting especially sleep tracking but also activity and nutrition tracking. In turn, the members of the third latent class are unlikely to have adopted any of the four self-tracking technologies, with the potential exception of exercise tracking, but they are extremely likely to be interested in adopting activity, sleep, and nutrition tracking as well as potentially also exercise tracking if not having already adopted it. Finally, we can see that the members of the fourth latent class are extremely unlikely to have adopted or being interested in adopting any of the four self-tracking technologies, with the slight exception of exercise tracking.

		LC1	LC2	LC3	LC4
Exercise tracking	Not adopted	0.000	0.533***	0.018	0.920***
	Interested	0.198*	0.191***	0.664***	0.029
	Adopted	0.802***	0.275***	0.319***	0.051**
Activity tracking	Not adopted	0.000	0.445***	0.000	0.982***
	Interested	0.011	0.389***	0.935***	0.018
	Adopted	0.989***	0.166***	0.065	0.000
Sleep tracking	Not adopted	0.068	0.431***	0.041	0.988***
	Interested	0.547***	0.509***	0.934***	0.009
	Adopted	0.385***	0.060**	0.024	0.003
Nutrition tracking	Not adopted	0.235*	0.690***	0.027	0.996***
	Interested	0.582***	0.290***	0.886***	0.000
	Adopted	0.183**	0.019	0.087**	0.004

Table 8: Results of the latent class analysis

The model estimation results also include the most likely latent class membership of each respondent, which can be used to approximate the absolute and relative sizes of the latent classes. In terms of size, the fourth latent class was found as the largest of the four (43.6 % of population), followed by the second latent class (33.6 % of population), the third latent class (15.8 % of population), and finally the first latent class (7.0 % of population). In addition, the most likely latent class memberships were also used to examine the potential dependencies of latent class membership on gender and age in similar manner than in the previous sub-section.

Table 9 reports the sizes of latent classes separately for men and women. When the statistical significance of the potential differences in these sizes was tested with the Pearson's X^2 test, its results rejected the null hypothesis of no difference ($X^2(3) = 8.238$, $p = 0.041$), thus suggesting a dependency between gender and latent class membership. However, when using the Pearson's residuals to examine this dependency in more detail, a statistically significant difference was found only in the fourth latent class, which was more dominated by men than women. In contrast, the second and third latent class seemed to be more dominated by women than men, but these differences were not statistically significant. The first latent class practically consisted of an equal number of men and women.

	Men		Women	
	%	Residual	%	Residual
Latent class 1	6.8	0.010	6.8	-0.010
Latent class 2	30.6	-1.755	36.4	1.755
Latent class 3	13.6	-1.500	17.4	1.500
Latent class 4	49.0	2.766**	39.4	-2.766**

Table 9: Gender differences between the latent classes

Table 10 presents the mean age of the members of each latent class. When the statistical significance of the potential differences in the mean ages was tested with the 1-ANOVA test, its results once again rejected null hypothesis of no differences ($F(3, 820) = 8.988$, $p < 0.001$), thus suggesting a dependency between age and latent class membership. Also in this case, the normality assumption was not met in any of the latent classes but the homoscedasticity assumption was met in all of them. When examining this dependency in more detail with the Tukey's test, statistically significant differences were found only between the mean age of the fourth latent class and the mean ages of all the other three latent classes. In the first and third latent classes, the mean ages were about 6–7 years lower in comparison to the fourth latent class, whereas in the second latent class, the mean age was about three years lower in comparison to the fourth latent class.

	Mean (years)	SD (years)	Mean differences (years)			
			LC1	LC2	LC3	LC4
Latent class 1	43.6	14.5	–	-2.7	1.2	-5.8*
Latent class 2	46.3	14.9	2.7	–	3.9	-3.1*
Latent class 3	42.4	13.7	-1.2	-3.9	–	-7.1***
Latent class 4	49.5	14.6	5.8*	3.1*	7.1***	–

Table 10: Age differences between the latent classes

5 Discussion and Conclusions

In this study, we examined the adoption and adoption interests of four self-tracking technologies related to exercise, activity, sleep, and nutrition tracking from both single technology and multiple technology perspectives and by concentrating especially on the potential gender and age dependencies in their adoption rates and adoption patterns. From single technology perspective, we found that the adoption rates of all the four self-tracking technologies still remained relatively low. Exercise tracking had the highest adoption rate of about 20–25 %, which was expected as this technology has the longest history of the four. For example, the first wireless wearable heart rate monitors were launched already in the early 1980s (Polar Electro, 2016), whereas most of the modern activity trackers, such as Fitbit, date back to the late 2000s or early 2010s (TechCrunch, 2009). However, although having not yet adopted, many consumers were interested in adopting self-tracking technologies. Sleep tracking had an interest rate of about 40 %, followed closely by activity and nutrition tracking with interest rates of about 30 %. Also some clear gender and age dependencies were observed. In terms of gender, women seemed to be more interested in adoption but men actually being more apt adopters with the exception of activity tracking. In terms of age, the non-adopters with no adoption interests were found to be slightly older in comparison to the adopters and those interested in adoption in the case of all the four self-tracking technologies.

From multiple technology perspective, we were able to identify four different consumer segments with distinct adoption patterns. We interpret and label the first of these segments as “pro-trackers” because it consisted of individuals who typically had adopted all or almost all of the four self-tracking technologies or at least were very interested in their adoption. As such, they seemed to be very into the whole self-tracking phenomenon and potentially members of the quantified self community. The second segment is the most ambiguous of the four and we interpret and label it cautiously as “semi-trackers” because the individuals in it clearly lagged behind the previous segment in terms of the actual adoption and adoption interests of all the four self-tracking technologies but seemed to be on a way of becoming more and more active self-trackers based on their adoption and interest rates. This segment was also found to be more dominated by women than men. The third segment is interpreted and labelled as “interested” because it consisted of individuals who had not yet actually adopted any of the four self-tracking technologies, with the potential exception of exercise tracking, but had extremely high adoption interests towards all of them. This unspecified nature of the interests would seem to imply that these individuals were actually not so familiar with the whole self-tracking concept in comparison to the previous two segments but simply liked the general idea of being able to track various aspects of themselves. This was the segment with the lowest mean age and also more dominated by women than men. Finally, we interpret and label the fourth segment as “non-trackers” because the individuals in it were clearly non-adopters of and not interested in any of the four self-tracking technologies, thus suggesting that the whole concept of self-tracking most likely felt strange or awkward to them. This segment was found to be significantly more dominated by men than women and also having the highest mean age, which is in line with our previous findings from single technology perspective.

An alternative interpretation of the segments can also be drawn from the theorisation by Rogers (2003) that the potential adopter population of an innovation can be divided into five different adopter categories based on their innovativeness (i.e., relative time of adoption): innovators (2.5 % of population), early adopters (13.5 % of population), early majority (34.0 % of population), late majority (34.0 % of population), and laggards (16.0 % of population). When these five adopter categories are compared to the four segments we identified in this study, a striking resemblance can be observed both in terms of adopter characteristics and category proportions. Therefore, “pro-trackers” may also potentially be interpreted as the innovators or as a combination of innovators and early adopters of self-tracking technologies, “semi-trackers” as the early majority, “interested” as the more innovative part of the late majority, and “non-trackers” as a combination of the less innovative part of the late majority and laggards.

From the aforementioned findings, three main practical implications can be drawn. First, there seem to be considerable business opportunities for the providers of self-tracking technologies especially among the slightly more female than male dominated segments of “semi-trackers” and “interested”, who were found to constitute almost half of our sample. In them, the adoption rates of self-tracking technologies still remained very low but the interest rates very high. Of the two, the most potential segment is probably the "semi-trackers", not only because of its larger size, but because its members are more likely to already have experience on some self-tracking technologies and therefore more easily persuaded into adopting also others. In contrast, the members of the "interested" segment with a very unspecified initial interest towards the self-tracking concept in general may be more challenging to be converted into actual adopters of specific self-tracking technologies.

Second, if the identified segments are interpreted as adopter categories in accordance with the theories of Rogers (2003), then the resulting temporal connection between the segments can potentially be used to extrapolate the future adoption of each of the four self-tracking technologies. In addition to such macro-level predictions, it may also be used on a micro-level to explain how the adoption process of these technologies is likely to progress in the case of an average consumer: first from a "non-adopter" with no adoption interests to an "interested" with an initial interest towards the self-tracking concept in general and potentially also some initial experiences of exercise tracking, then to a "semi-tracker" with more specified interests and also more experiences of exercise as well as activity tracking, and finally to a "pro-tracker" with a varied usage and vast interest towards all the four technologies. How fast or slowly a particular individual transits from one phase to another on this "adoption path", is ultimately determined by his or her innovativeness.

Third, regarding to this "adoption path", there are also indications that exercise tracking plays a central role in the aforementioned transitions from one phase into another. As mentioned above, exercise tracking was found as the most commonly adopted or at least one of the most commonly adopted self-tracking technology not only among "pro-trackers", but also among "semi-tackers" and "interested". Although our data does not tell anything about the temporal order in which the different technologies were adopted, this could imply that exercise tracking is typically the first or one of the first self-tracking technologies that individuals adopt and which then introduces them to the whole concept of self-tracking and increases their interest towards other self-tracking technologies. Of course, over time, this increasing interest towards other self-tracking technologies may cause some individuals to actually switch exercise tracking to these other technologies and result in discontinued adoption. For example, among "pro-trackers", we found that the adoption rate of activity tracking was actually higher than the adoption rate of exercise tracking, which could be an indication of such switching. Respectively, among "semi-trackers" the relative difference between the adoption rates of exercise and activity tracking was actually smaller than among "interested", which could also be caused by similar kind of switching. However, in spite of whether or not such switching occurs at a later occasion, the central role of exercise tracking as an introductory technology obviously means that the most potential segments for adopting activity, sleep, and nutrition tracking technologies are the consumers who already track their exercise in one way or another, making it more sensible for businesses to take this segment as a target of different kinds of marketing activities rather than consumers who do not yet track any aspect of themselves. Of course, it must be noted that this central role of exercise tracking may change over time as technologies continue to develop and new consumer generations enter the market. For example, among “semi-trackers”, one explanation for the relatively more even adoption rates of exercise and activity tracking in comparison to “interested” may also be the fact that activity tracking has already begun to take the role of exercise tracking as an introductory technology.

Finally, as a main theoretical implication, the findings of the study underline the value of the utilised multiple technology perspective in examining technology adoption in terms of being able to highlight the potential dependencies in the adoption patterns as discussed above. Although this perspective has been commonly used in adoption studies especially in the agricultural context (e.g., Dorfman, 1996), the studies utilising it in the context of information systems (IS) have been relatively rare, with most studies and theories, such as TAM, UTAUT, and UTAUT2, typically taking only a single technology perspective. However, this study can hopefully, for its part, act as an impetus for its more prevalent utilisation also in the IS context.

6 Limitations and Future Research

The main limitation of this study is that it concentrated on examining the adoption of self-tracking technologies only in the case of Finnish consumers and by using a relatively simple research setting and operationalisations of the adoption and adoption interest concepts, which did not consider, for example, how frequently the four self-tracking technologies were used or how frequently the data collected by using them was viewed or otherwise accessed. This obviously limits the generalisability of its findings and calls for future studies in which these limitations are addressed. In these studies, more attention should also be paid on potential sampling biases in terms of, for example, technology readiness and lifestyle issues. In addition to the macro-level perspective taken in this study, future studies would also benefit from taking a more micro-level perspective to the topic and examining, for example, what kind of concrete antecedents can be found behind the decisions of individual consumers to adopt or not to adopt a specific self-tracking technology. However, also in this case, it is preferable to do such examinations from a multiple rather than single technology perspective in order to be able to perceive the potential homogeneity or heterogeneity in these antecedents between different technologies.

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Appendix A: Question Wording

Do you track the following aspects of your health behaviour with a technological tool (e.g., a smart phone or smart bracelet) or which of them would you be willing to track with technological tools in the future?

I already track:
- □ Exercise (duration, amount, strain, calories, etc.)
- □ Daily physical activity (steps, calories, etc.)
- □ Amount and quality of sleep
- □ Eating and nutritional intake
- □ I cannot say

I would be interested in tracking:
- □ Exercise (duration, amount, strain, calories, etc.)
- □ Daily physical activity (steps, calories, etc.)
- □ Amount and quality of sleep
- □ Eating and nutritional intake
- □ I cannot say