Technology readiness, UTAUT2 and continued use of digital wellness services - A configurational approach

József Mezei
Åbo Akademi University
jozsef.mezei@abo.fi

Anna Sell
Åbo Akademi University
anna.sell@abo.fi

Pirkko Walden
Åbo Akademi University and Institute for Advanced Management Systems Research
pirkko.walden@abo.fi

Abstract

Digital wellness is a multi-disciplinary domain that makes use of digital and mobile technologies in order to provide personalized services for the users to improve their mental and physical well-being. In order to understand the main drivers of continued usage of digital wellness services, we make use of the well-established Unified Theory of Acceptance and Use of Technology (UTAUT2) and extend it by considering user's technology readiness (TR). Survey data is collected from 162 Finnish young elderly who participate in a research program and use a digital wellness application. With Fuzzy-set Qualitative Comparative Analysis combinations of UTAUT2 dimensions and TR that lead users to continue or stop using digital wellness services, are identified. The results show that technology readiness can contribute to our understanding of users' continued usage behavior, both as an independent dimension and when combined with some of the UTAUT2 dimensions. Contrasted with previous research, our study confirms the importance of Effort expectancy whereas the impact of Performance expectancy is found to be less direct.

1. Introduction

Reasons to adopt and continue using digital technology remain one of the central research interests of information systems researchers. Different acceptance models, such as TAM and UTAUT2, have formed the backbone of this research stream. These models place focus on an individual's perceptions of different aspects of the studied technology. Another view can be gained by looking at individuals' personal characteristics in relation to technology. The Technology Readiness Index (TRI) 2.0 operates from this viewpoint [13]. Technology readiness is described as an "individual-level characteristic that does not vary in the short term", comprised of motivators and inhibitors which together determine an individual's predisposition to use new technologies [13 p. 61]. TRI 2.0 has been found to be reliable, valid and useful as a customer segmentation tool, and consequently, many of the studies making use of technology readiness are segmentation studies (see e.g. [17, 18, 19]). In turn, UTAUT2 has been applied to numerous different contexts, demographics and technologies to investigate behavioral intention to adopt or use a technology, with the assumption that intention leads to actual use.

In this study, we combine TR (individual propensity to adopt and use technology) with UTAUT2 (an individual's perceptions of a technology) to gain a more complete picture of reasons to adopt and use technology. Further, we utilize Fuzzy-set Qualitative Comparative Analysis (FsQCA) methodology, which enables us to extract deep insight by examining different configurations leading users to continue or discontinue using a digital service. This approach is novel, as TR and UTAUT2 have not previously been used in combination and analyzed with FsQCA. In contrast to the typically used regression-based methods analyzing the effects of individual variables, FsQCA allows us to understand the effects of combinations of variables, e.g., whether perceived usefulness and technology optimism *together* lead to use. Our data was collected within a longitudinal research program focused on supporting the wellness of young elderly - people in the age category 60 to 75 - through introducing digital wellness services. The data presented in this article was collected from participants who had already been part of the program for several months and were current users of the digital wellness service, enabling us to study actual use instead of adoption. We propose that combining TR and the UTAUT2 dimensions enable us to better understand intention to continue or discontinue using a digital service. Using FsQCA, we can better capture and understand complex and even paradoxical attitudes towards technology.

2. Literature review and propositions

The continued use of digital wellness technologies specifically by elderly or young elderly consumers has not been studied much. In [32], utilizing a smaller

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sample of the data used in the study at hand, the researchers studied continued use over an 18-month period, and found through PLS-SEM that UTAUT2 explains use intention well. The effects of hedonic motivation and habit emerged as significant, whereas the effect of social influence was not. [36], studying elderly diabetics using a digital health wearable, found perceived usefulness, perceived ease of use, perceived irreplaceability, perceived credibility, compatibility and social influence to be significant factors for continued use. When expanding the scope to studies examining other age groups, some more results emerge. In a literature review [33] examine continued use of mHealth applications. They find that most studies in the domain have made use of either Information Systems Continuance Model (ISCM) or UTAUT2. Central factors affecting continued use are found to be satisfaction, perceived usefulness and perceived service quality. There is some evidence also on the effect of perceived ease of use and hedonic motivation. [34] found in a netnographic study that perceived ease of use and perceived usefulness emerge as important factors for continued use, but he also brings forth more novel factors such as fashionability and complementary technologies. Also [35] identifies perceived usefulness and ease of use as important factors, in addition to hedonic factors and context-related factors such as observational learning. In summary, the role of perceived usefulness has been consistently identified to be an important factor for continued use, and there is also evidence on the roles of perceived ease of use, hedonic motivation, habit and social influence.

UTAUT2 aims to explain use of information technology in a consumer context [15]. TRI 2.0, on the other hand, measures customer traits influencing a person's likelihood to adopt and use technologies to accomplish goals [16]. FsQCA is an emerging method in Information systems [12] and it has not, to our knowledge, previously been applied to the combination of technology readiness and the UTAUT2 dimensions. Jahanmir et al. [14] apply FsQCA to a combination of personal and perceptual factors in order to explain continued use of technology, but their study encompasses neither technology readiness nor UTAUT2 dimensions.

Almost as rare are studies where FsQCA has been used to investigate the effect of the UTAUT2 dimensions and combinations of them on technology use and adoption. In the following, we present the most relevant previous research. Duarte and Pinho [4] investigate the UTAUT2 dimensions in relation to adoption of mobile health technologies. They contrast results from PLS-SEM and FsQCA and discover that in the structural equation modelling approach, performance expectancy (PE), hedonic motivation (HM) and habit predict mobile health technology adoption, while the FsQCA uncovers six causal configurations leading to adoption. In the FsQCA, no single condition is found to explain adoption on its own. The configurations with the highest consistency scores are combinations of three or more of the UTAUT2 dimensions. The strongest configuration combines PE, effort expectancy (EE), social influence (SI), facilitating conditions (FC) and habit. When analyzed jointly with demographic variables, some differences related especially to gender and education emerge. The authors conclude that performance expectancy is the strongest predictor in both PLS-SEM and FsQCA analyses, being present in all configurations.

In a similar approach, Liang et al. [5] investigate the impact of the UTAUT2 dimensions on technology adoption in an autonomous vehicle context. In assessing their structural model, they find only PE, price value (PV) and habit to be significant predictors of behavioral intention. In analyzing necessary conditions, they find that PE and EE are alone necessary to explain adoption. Further, they find twelve configurations leading to high behavioral intention and seven configurations with a negative outcome. PE is present in nine of the twelve positive configurations. EE is likewise found to be important, present in eight positive configurations. While not central, SI, FC and HM are present in several positive configurations and their absence is required in several negative configurations.

Some FsQCA studies make use of the original version of the UTAUT model, such as [2], [10] and [11], or TAM [3]. The original UTAUT model comprises the PE, EE, SI and FC dimensions [25], whereas the TAM model only includes perceived ease of use, equivalent to EE, and perceived usefulness, equivalent to PE [30]. In a rare study combining technology readiness and parts of an acceptance model, Roy et al. [9] examine customer attitudes towards smart technologies in retail through a combination of technology readiness, and the perceived usefulness and perceived ease of use dimensions of TAM, in addition to the retail-oriented dimensions superior functionality and perceived adaptiveness. Perceived usefulness is found to be a core condition present in all configurations explaining a positive attitude towards smart retail technologies. Perceived ease of use is a noncore condition present in all positive configurations. Also, low perceived usefulness is present in all configurations related to negative attitude. Technology readiness or absence thereof is present in some configurations leading to both positive and negative attitudes.

Taken together, these previous FsQCA studies all identify performance expectancy or perceived usefulness as an important factor leading to intention to adopt or a positive attitude, present in most configurations. Effort expectancy or perceived ease of use, social influence, facilitating conditions, habit and hedonic motivation are also influential. It is worth noting that the previous studies all investigate behavioral intention to adopt, differing from the study at hand where focus is on behavioral intention to continue use.

Apart from [9], we could not identify studies making use of FsQCA and technology readiness. In addition to the previously mentioned segmentation studies, technology readiness has been studied as an antecedent to perceived ease of use and perceived usefulness and consequently to technology use [20]. In this vein some research has focused on creating a model combining technology readiness and the technology acceptance model to an integrated Technology Readiness and Acceptance Model (TRAM), thus combining perceptual and personal factors [21, 23, 24]. Some researchers have extended the model, e.g. [22] who incorporated health consciousness to adapt the model to a health behavior context.

Previous research has highlighted the role of both perceptual and personal factors in influencing an individual's adoption and continued use of technology, but typical studies have investigated individual causal factors. We suggest that a configurational analysis will enable us to unveil more complex patterns behind the intention to continue using digital services, and we put forth the following propositions:

Proposition 1. Different combinations of Technology readiness and the UTAUT2 dimensions lead to high/low level of intention to continue using digital wellness services for young elderly

Proposition 2. Technology readiness and the UTAUT2 dimensions are not, by themselves, necessary to influence continued use of digital wellness services for young elderly

Proposition 3. Technology readiness and the UTAUT2 dimensions are not, by themselves, sufficient to influence continued use of digital wellness services for young elderly

3. Data and methodology

In this section, we will briefly present the data collection process with a basic descriptive analysis together with the chosen data analysis methodology, FsQCA. All the computations were performed, and visualizations generated by various packages of the statistical programming language R [1]. We note here, that in this paper we use the terminology 'presence' and 'absence' of a variable, in line with the literature, for high and low values. For example, we talk about the presence (absence) of continued usage, when a high (low) value is observed.

The empirical data was collected in the years 2019 and 2020. The data collection process was part of a several years long initiative aimed at understanding the attitudes and behavior of young elderly towards technology, in particular physical activity programs. The participants join the research program throughout the years and in this study, we have chosen those who joined the program between June 2019 and June 2020. The data was collected in two subsequent surveys, with the second one carried out 4 months after the first, when the participants already had an experience and opinion about the physical activity program as well as the application in use. The number of participants considered in the beginning of the analysis was 265 but after checking for and treating missing values, there were 162 valid responses left for further analysis.

The study was conducted in Finland, with 95% of the respondents completing the questionnaire in Finnish, with the remaining 5% in Swedish. As the aim of the research project was to understand the behavior and preferences of the young elderly age group, the average age of the respondents is 71 years, with standard deviation of 4.2 years. Regarding the gender of the participants, 62% were females and 38% males. We also collected residential data and found that, 12% of the respondents are from a large city or suburb (more than 100,000 inhabitants), 31% are from a medium city or municipality (20,000-100,000 inhabitants), 30% are from a small municipality (less than 20,000), and 27% are from the countryside.

3.1. Measurement model

The constructs used in the study were measured using validated items from previous technology readiness related studies, based on the Technology Readiness Index (TRI) 2.0 presented by [13] and the unified theory of acceptance and use of technology (UTAUT2, [15]). All items were measured on a 5-point Likert-scale, ranging from 'Strongly disagree' to 'Strongly agree'. The questionnaire was evaluated, and pilot tested to identify and correct for any ambiguous wording or expressions. The list of items is presented in

Appendix 1. In the analysis, after the initial data cleaning and preparation, the four dimensions of optimism, innovativeness, discomfort and insecurity were combined into a higher-level Technology Readiness construct. In previous literature, this has been performed similarly for example by [26, 27 and 28] when looking at the interrelations of Technology Readiness and dimensions from the original Technology Acceptance Model. Regarding the components of the UTAUT2 framework, Price Value was excluded in the research as the participants got the application for free Confirmatory and reliability analyses were performed on the data; the detailed results are presented in the Appendix). There are several items identified with standardized loadings below the recommended 0.5, consequently they were removed from further analysis: one item for innovativeness, insecurity and discomfort, and two items for facilitating conditions. The Cronbach alpha indicator showed acceptable indices of internal consistency for all constructs exceeding the threshold value of 0.70.

3.2. Data preprocessing for FsQCA

As the first step of the analysis, data calibration is performed using a fuzzy transformation. The items for each construct were combined using arithmetic mean operator to obtain an average score. Furthermore, to obtain a single value for Technology Readiness, the average scores for Optimism, Innovativeness, Discomfort and Insecurity were combined using arithmetic mean. After we obtained the aggregated values, direct calibration approach was utilized, as it allows for rigorous analysis, reproducibility and validation [6]. In order to transform the original values into fuzzy membership values in the [0,1] interval, three threshold values corresponding to non-membership (transformed value 0), cross-over point (transformed value 0.5) and full membership (transformed value 1) need to be determined. In this study, we utilized some established statistical measures, and calculated the three thresholds as the 5%, 50% and 95% quantiles of the variables. Intermediate points were transformed into fuzzy membership using a logistic function based on the three calculated threshold values. The calibration thresholds for the variables are presented in Table 1. For example, when the values of Effort Expectancy are transformed into (i) 0, when lower than 2.75, (ii) 1, when at least 5, (iii) 0.5, when equal to 4.25, and (iv) intermediate values based on a logistic function [31] otherwise.

Table 1 Calibration threshold values with non-membership (5%), crossover value (50%) and full membership (95%)

	5%	*50%*	*95%*
Optimism	1.75	3.50	4.75
Innovativeness	1.00	2.67	4.33
Insecurity	1.67	3.50	5.00
Discomfort	1.25	3.05	4.43
Effort Expectancy	2.75	4.25	5.00
Performance expectancy	1.81	3.50	5.00
Social Influence	1.00	3.00	4.75
Facilitating Conditions	3.00	4.00	5.00
Hedonic motivation	2.06	3.75	5.00
Habit	1.50	3.50	4.75
Behavioral Intention	2.31	4.00	5.00

The next step of the analysis is to identify potentially necessary conditions [7]. Identifying a variable as necessary would imply that whenever continued intention has high values, the antecedent condition should (almost) always have high values. The results are presented in Tables 2 and 3. In order to determine whether a variable is a necessary condition, consistency and coverage measures are calculated. Consistency values higher than 0.9 indicate the presence of a necessary condition as suggested by [8]. Coverage captures the importance of the relationship; the lower it is, the smaller is the number of cases to which the identified relationship is applicable. In Tables 2 and 3, we present the results for identifying necessary conditions for both high and low level of continued intention. The measures are calculated for both the presence and the absence (indicated with 'not' in the tables) of each construct. First, we note that, as expected, higher values (presence) of each of the variables are more consistent with higher continued intention. For example, a respondent who indicates high level of Technology Readiness will also have high level of continued usage. Conversely, the absence of Effort Expectancy is more likely to occur together with low level of continued usage. Furthermore, as we can observe from the tables, while there is no single variable with consistency value higher than 0.9, there are several values very close to this recommended threshold. This indicates that there are some variables that are required for high/low level of continued intention. In particular, as we will also see in the results of the FsQCA analysis, this result is interesting for some variables in relation to the absence of continued usage intention: low performance expectancy and low hedonic motivation have consistency values over 0.85 with low outcome values. As a summary, while we can observe some very high values close to the recommended threshold, we can still state that Proposition 2 holds, i.e., there is no single antecedent of continued intention that can be identified as necessary.

Table 2 Necessity analysis for high values of the outcome variable (presence on continued usage)

Construct	Consistency	Coverage
TR	0.71	0.75
not TR	0.59	0.65
EE	0.73	0.74
not EE	0.55	0.86
PE	0.79	0.89
not PE	0.49	0.59
SI	0.66	0.70
not SI	0.64	0.71
FC	0.78	0.84
not FC	0.50	0.76
HM	0.77	0.89
not HM	0.53	0.62
HT	0.80	0.88
not HT	0.50	0.61

Table 3 Necessity analysis for low values of the outcome variable (absence of continued usage)

Construct	Consistency	Coverage
TR	0.75	0.61
not TR	0.78	0.67
EE	0.61	0.50
not EE	0.78	0.68
PE	0.54	0.43
not PE	0.86	0.76
SI	0.63	0.50
not SI	0.77	0.69
FC	0.60	0.47
not FC	0.80	0.73
HM	0.55	0.46
not HM	0.87	0.74
HT	0.56	0.45
not HT	0.75	0.75

4. Results

In this section, the main results of the FsQCA analysis are presented. The necessity analysis highlighted that there are several variables that have reasonably strong connection to continued intention. This indicates that we may not obtain very complex combinations as solutions, but rather simpler configuration solutions consisting of a couple of variables at most. As the basis of performing the analysis, i.e., identifying the configurations that are sufficient to result in the presence/absence of continued usage value, the truth table needs to be constructed. This requires calculating the frequency of all the possible combinations of the presence (over 0.5) and absence (below 0.5) of the antecedent variables. As we have seven antecedent variables, there are 2^7=128 possible combinations. As there are just over 160 data points in our dataset, one cannot expect to have all the theoretically possible configurations present, but this data size should be sufficient to allow for observing the most relevant ones. In the data, we found at least one corresponding respondent for 58 of the 128 possible configurations (45% of all the possible configurations). After the truth table is constructed, for each configuration we need to assign a label indicating whether it corresponds to the presence or absence of the outcome variable. The value of consistency quantifies the extent to which a given configuration ‘agrees’ (co-occur) with high/low values of the outcome variable. While there is a widely employed cut-off value (0.75) recommended by [29], as consistency is not typically associated with any corresponding statistical significance test, it has been pointed out in the literature that the optimal consistency value should be determined after carefully considering the underlying dataset. In this study, we still performed extensive testing with possible configuration values, and we established cut-off values that are stable in the sense that a change of +-4% in the determined value would not change the resulting configuration solutions. After the testing, the cut-off value for high outcome was determined as 0.8, and for low outcome as 0.75. Furthermore, considering the limitations posed by the size of dataset, we set the frequency cut-off for configurations to be included in the analysis as 1 in order to retain a sufficient number of cases. The results of the analysis are presented in Tables 4 and 5 for the presence and absence of continued use intention, respectively. In the tables, ● and Δ stands for the presence and absence of a condition (row) in the configuration (column). For example, in Table 4, configuration 2 implies that the presence of Effort Expectancy is sufficient for having high continued usage intention, while configuration 3 in Table 5 implies that the absence of Effort Expectancy and Facilitating Conditions is sufficient for the absence of continued usage intention (i.e. intention to abandon the service). The numbers in the first row of Table 4 refer to the four configurations (combined consistency: 0.79, combined coverage: 0.92), and the numbers in the first row of Table 5 refer to the six configurations (combined consistency: 0.73, combined coverage: 0.96).

Table 4. Solution configurations for high continued usage intention of digital wellness services (DWS).

Variable	1	2	3	4
TR				●
EE		●		
PE				
SI	●			
FC			●	
HM				
HT				
Consistency	0.82	0.82	0.84	0.82
Coverage	0.73	0.74	0.78	0.72

Table 5. Solution configurations for the absence of high continued usage intention of DWS.

Variable	1	2	3	4	5	6
TR				Δ	Δ	
EE			Δ	Δ		Δ
PE	Δ					
SI						Δ
FC			Δ		Δ	
HM		Δ				
HT						
Consis-tency	0.76	0.73	0.78	0.78	0.83	0.80
Coverage	0.86	0.87	0.68	0.66	0.66	0.64

As we can see from the tables above, there are 4 and 6 configurations leading to high and low outcome values, respectively. One can observe that the outcome of the analysis confirms the expectations hypothesized above about the possible structure of the configurations. Namely, that there are no configurations that involve more than two antecedent conditions at a time, and in particular for high outcome values, we have only single conditions acting as sufficient configurations. Regarding the quality of the solutions however, we can still claim to have obtained high performance. In terms of consistency, for each individual configuration we obtained values above 0.8 for the presence and above 0.75 for the absence of the outcome. The overall consistency values are above 0.70, indicating that the identified configurations explain more than 70% of variations of the data related to the outcome variable. Moreover, the coverage value, the number of cases (in a fuzzy sense) that are covered by a configuration, are extremely high, over 0.95, indicating that these small set of configurations can account for almost all the observable behavioral patterns.

5. Discussion

In the following, we will discuss the results presented in the previous section. We identified a set of configurations that offer alternative explanations on why users intend to (not) continue using digital wellness services. This highlights the principle of equifinality, i.e., the presence of co-existing alternative explanations to understand an underlying phenomenon. Furthermore, the obtained configurations clearly show the asymmetric nature of the phenomenon as the configurations for low and high level of intention to continue using digital wellness services are not simply the opposite of each other. Before looking at the individual configurations, we can make some general observations considering the structure and alignment of the obtained solutions. This research introduced the idea of integrating Technology Readiness with the dimensions of the UTAUT2 model in a configurational framework. It is an important finding that Technology Readiness indeed plays a role in understanding user behavior. As the solution configurations show, Technology Readiness as a causal antecedent appears in at least one configuration for both the presence and absence of intention to continue using digital wellness services. Second, with regards to the original constructs of the UTAUT2, we can observe in Tables 4 and 5 that all of them appear in at least one configuration except for Habit. As Habit has not been part of the original UTAUT model, this result shows that while it definitely plays a role in the use behavior of many information systems, in particular the use of various digital services, our data does not show any evidence on Habit playing an important role in young elderlies' intention to continue using digital wellness services. These observations together support Proposition 1: different configurations of technology readiness and (most of) the constructs of the UTAUT2 model lead to intention to continue using digital wellness services.

5.1. Configurations for high level of intention to continue using digital wellness services

As presented in Table 4, four configurations can be identified as being in causal relationship with the presence of the outcome variable, i.e., configurations that lead to continued use of digital wellness services. The identified configurations take a very simple form as all of them consist of a single variable identified as sufficient to reaching high level of intention to continue using digital wellness services. The configurations identify four of the seven possible variables as sufficient: high Technology Readiness, Effort Expectancy, Social Influence and Facilitating Conditions lead to the outcome of interest. This is in high contrast with existing studies on investigating user behavior through the lens of UTAUT2 model or Technology Readiness [5, 9], in which identified configurations typically take a more complex form. In this study, the collected data shows a more straightforward, but not trivial, picture of why young elderly continue to use digital wellness services: if they perceive at least one of the four identified, core antecedents positively enough, this is sufficient to drive further use of the service.

These observations highlight the finding that Proposition 3 does not hold, at least for the case of the presence of continued use. As pointed out above, the results highlight the importance of considering Technology Readiness together with the original UTAUT2 constructs, and furthermore identifies Effort Expectancy, Social Influence and Facilitating Conditions as the constructs with the most causal explanatory power. While Habit does not seem to play any role based on the data we collected, this is still a very interesting finding in relation to Performance Expectancy and Hedonic motivation, two dimensions that are typically identified as important ones within the UTAUT 2 model. However, as we will discuss in the following, these two variables play a reverse role, as they are crucial in understanding the lack of intention to continue using digital wellness services.

Regarding the quantitative performance of the analysis, as highlighted above, the result can be claimed to be sufficiently stable as a slight increase or decrease would not impact the configuration solution set. Furthermore, we achieved very high individual consistency values and overall consistency, indicating good explanatory power. Finally, the coverage values are also very high (above 0.7), which infers that there is a large overlap in terms of the cases covered by the individual solution configurations. This is not surprising as all the configurations consist of a single condition.

5.2. Configurations for low level of intention to continue using digital wellness services

According to Table 5, and compared to the four configurations in Table 4, we obtained a slightly more complex set of configurations when understanding the causal antecedents of the absence of intention to continue using digital wellness services. While configurations were still found to be less complex than one would expect (at most two antecedent conditions in any configuration), we obtained a wider variety of causal explanations. The first main observation concerns configurations 1 and 2 in Table 5: the absence of Performance Expectancy and/or Hedonic Motivation results in the user not continuing to use digital wellness services. This leads us to disprove Proposition 3 also in this second part of the analysis, as we identified some of the constructs that alone are sufficient to reach the absence of the outcome of interest. Furthermore, this shows that Performance Expectancy and Hedonic motivation are indeed crucial, however not by contributing to the understanding of positive continued used directly but by shedding light on why users stop using a service. This highlights a crucial aspect of configurational modeling, and in particular FsQCA, namely asymmetry: the configurations associated to the presence and absence of an outcome of interest are not simple transformations of each other.

The next interesting observation relates to the three constructs Effort Expectancy, Facilitating Conditions and Technology Readiness. As the results show in Configurations 3-5 in Table 5, the lack of any of these three conditions alone is not sufficient to ensure the absence of continued use. However, combining any two of them is enough to ensure the absence of the outcome variable. This is interesting when considered together with the results in Table 4, indicating that these three constructs are of particular importance when understanding both positive and negative user attitude towards continuing to use digital wellness services. The final configuration in Table 5 illustrates that the lack of Social Influence also plays a role when combined with the absence of Effort Expectancy.

As for the strength of the established configurations, we can observe in Table 5 sufficiently high values (above 0.73 in all the cases), with less overlapping but still explaining 96% of the data points.

6. Conclusions

In this article, for the first time in the literature we integrated Technology Readiness with UTAUT2 to gain an understanding of why users continue or stop using digital wellness services. Motivated by recent studies on the use of digital services analyzed through the lens of the concept of various dimensions of the recently introduced TRI 2.0 framework [13], we propose to make use of this tool in combination with one of the most widely used technology acceptance models, UTAUT2. By combining these two in a configurational approach, we aimed to obtain a deep understanding of the reasons that drive users to continue or stop using digital wellness services. To test the proposal, we made use of data collected in a multi-year initiative aimed at introducing digital wellness services to young elderly in Finland. The longitudinal data allowed us to focus on continued use of the service rather than the adoption process.

In the empirical work, we made use of data collected over a two-year period from young elderly users of a digital wellness service. In order to make full use of the complex data structure, we opted to use a widely used quantitative configurational data analysis methodology, FsQCA. By analyzing responses from over 160 participants, we identified configurations as the combinations of Technology Readiness and constructs of the UTAUT2 model, that are sufficient for a user to continue or stop using a digital wellness service. The results have several important implications extending our understanding of the use of digital wellness services. First, we found that there is no single variable that could be considered as a necessary condition for users to continue or stop using digital wellness services, although some variables, such as Performance Expectancy and Hedonic Motivation have very strong explanatory power.

Secondly, in contrast to most of the previous studies, we found that in most cases very simple configurations, involving at most two variables, are very powerful as sufficient conditions for the investigated outcome variable. In particular, when any one of the constructs Technology Readiness, Effort Expectancy, Social Influence or Facilitating Conditions is highly perceived by a user, it is a sufficient reason to continue using the digital wellness service. Thirdly, while Performance Expectancy and Hedonic Motivation are typically identified as constructs of core importance, we established this in the analysis in an indirect manner, i.e., we found that low perceived evaluations of the users along these two dimensions will lead to stop using the service. In other words, if the users do not find the service useful or fun, they will stop using it, but high evaluations are not in themselves sufficient reason to continue using the service. Most previous research studied adoption instead of continued use, which might explain the different role of PE and HM; perhaps their impact is more direct at the adoption stage.

Finally, the resulting solution configurations show very high performance, as they alone account for the explanation of user behavior in 92% and 96% of the cases when understanding users who continue and stop using digital wellness services, respectively. The study has several limitations. First, the study was conducted in Finland involving participants from the young elderly age group, thus we cannot claim that the results can directly be generalized for any other geographic region or age segment. It is conceivable e.g., that the roles of Social Influence and Facilitating Conditions are especially salient in this age group. Furthermore, there are several possible configurations of Technology Readiness and UTAUT2 constructs that do not appear in the utilized dataset. This implies that, while we controlled for the sensitivity of the FsQCA methodology with respect to different parameters, we may obtain different results after collecting more data. According to this, an important future research task will be to collect more data to further test and validate the presented results.

A1. Appendix

In the questionnaire, the respondents were asked to evaluate statements on a 5-point attitude scale. The following are the statements used in the article listed under the corresponding construct. Next to each construct and statement, some descriptive, reliability and validity measures are provided.

Optimism (Cronbach alpha: 0.82)

- *OPT1*: New technologies contribute to a better quality of life (mean: 3.7, standard deviation: 0.97, standardized loading: 0.77)
- *OPT2*: Technology gives me more freedom of mobility (mean: 3.2, standard deviation: 1.11, standardized loading: 0.64)
- *OPT3*: Technology gives people more control over their daily lives (mean: 3.5, standard deviation: 1.08, standardized loading: 0.75)
- *OPT4*: Technology makes me more productive in my personal life (mean: 3.2, standard deviation: 1.17, standardized loading: 0.77)

Innovativeness (Cronbach alpha: 0.78)

- INN1: Other people come to me for advice on new technologies (mean: 2.4, standard deviation: 1.3, standardized loading: 0.64)
- INN2: In general, I am among the first in my circle of friends to acquire new technology when it appears (mean: 2.5, standard deviation: 1.2, standardized loading: 0.76)
- INN3: I can usually figure out new high-tech products and services without help from others (mean: 3.1, standard deviation: 1.2, standardized loading: 0.66)
- INN4: I keep up with the latest technological developments in my areas of interest (mean: 3.6, standard deviation: 1.1, standardized loading: 0.36)

Discomfort (Cronbach alpha: 0.77)

- DIS1: When I get technical support from a provider of a high-tech product or service, I sometimes feel as if I am being taken advantage of by someone who knows more than I do (mean: 2.6, standard deviation: 1.1, standardized loading: 0.55)
- DIS2: Technical support lines are not helpful because they don't explain things in terms I understand (mean: 2.9, standard deviation: 1.2, standardized loading: 0.62)
- DIS3: Sometimes, I think that technology systems are not designed

for use by ordinary people (mean: 2.9, standard deviation: 1.3, standardized loading: 0.72)

- DIS4: There is no such thing as a manual for a high-tech product or service that's written in plain language (mean: 3.2, standard deviation: 1.3, standardized loading: 0.78)

Insecurity (Cronbach alpha: 0.70)

- INS1: People are too dependent on technology to do things for them (mean: 3.3, standard deviation: 1.1, standardized loading: 0.78)
- INS2: Too much technology distracts people to a point that is harmful (mean: 3.6, standard deviation: 1.2, standardized loading: 0.62)
- INS3: Technology lowers the quality of relationships by reducing personal interaction (mean: 3.3, standard deviation: 1.3, standardized loading: 0.65)
- INS4: I do not feel confident doing business with a place that can only be reached online (mean: 3.5, standard deviation: 1.3, standardized loading: 0.36)

Performance expectancy (Cronbach alpha: 0.92)

- PE1: DW app is useful to me in my daily life (mean: 3.5, standard deviation: 1.1, standardized loading: 0.72)
- PE2: By using DW app I achieve my PA goals more securely (mean: 3.5, standard deviation: 1.1, standardized loading: 0.68)
- PE3: By using DW app I achieve my PA goals faster (mean: 3.3, standard deviation: 1.1, standardized loading: 0.73)
- PE4: By using DW app I achieve my PA goals more efficiently (mean: 3.5, standard deviation: 1.1, standardized loading: 0.62)

Effort expectancy (Cronbach alpha: 0.81)

- EE1: It is easy for me to learn to use DW app (mean: 4.2, standard deviation: 0.9, standardized loading: 0.81)
- EE2: I find using DW app to be straightforward and intuitive (mean: 4.3, standard deviation: 0.9, standardized loading: 0.55)
- EE3: I find it easy to use DW app (mean: 4.3, standard deviation: 0.8, standardized loading: 0.73)
- EE4: It is easy for me to become a skillful user of DW app (mean: 3.8, standard deviation: 0.9, standardized loading: 0.65)

Social influence (Cronbach alpha: 0.91)

- SI1: People important to me think I should use DW app (mean: 3.1, standard deviation: 1.2, standardized loading: 0.81)
- SI2: People who influence my behaviour think that I should use DW app (mean: 2.9, standard deviation: 1.2, standardized loading: 0.74)
- SI3: People whose opinions I value think that I should use DW app (mean: 3.1, standard deviation: 1.1, standardized loading: 0.83)
- SI4: People who I trust think that I should use DW app (mean: 3.3, standard deviation: 1.1, standardized loading: 0.88)

Facilitating conditions (Cronbach alpha: 0.73)

- FC1: I have the necessary resources to use DW app (mean: 4.3, standard deviation: 0.8, standardized loading: 0.75)
- FC2: I have the necessary knowledge (skills) to use DW app (mean: 4.0, standard deviation: 1.0, standardized loading: 0.82)
- FC3: Using DW app is compatible with other technologies I use (mean: 3.6, standard deviation: 1.2, standardized loading: 0.28)
- FC4: If I encounter any problems using DW app, I get help from others when needed (mean: 4.2, standard deviation: 1.0, standardized loading: 0.34)

Hedonic motivation (Cronbach alpha: 0.89)

- HM1: Using DW app is fun (mean: 3.7, standard deviation: 1.0, standardized loading: 0.86)
- HM2: Using DW app is delightful (mean: 3.7, standard deviation: 0.9, standardized loading: 0.81)
- HM3: Using DW app is entertaining (mean: 3.3, standard deviation: 1.1, standardized loading: 0.77)
- HM4: Using DW app is pleasant (mean: 3.9, standard deviation: 0.9, standardized loading: 0.79)

Habit (Cronbach alpha: 0.81)

- HT1: Using DW app has become a routine to me (mean: 3.8, standard deviation: 1.1, standardized loading: 0.73)
- HT2: I am addicted to use DW app (mean: 2.6, standard deviation: 1.1, standardized loading: 0.70)
- HT3: I feel the need to use DW app (mean: 3.0, standard deviation: 1.2, standardized loading: 0.42)
- HT4: Using DW app has become natural to me (mean: 3.9, standard deviation: 1.1, standardized loading: 0.78)

Continued Use (Cronbach alpha: 0.89)

- BI1: I intend to continue using DW app in the future (mean: 4.0, standard deviation: 1.0, standardized loading: 0.67)
- BI2: I will try to continue using DW app in my daily life (mean: 4.1, standard deviation: 0.9, standardized loading: 0.69)
- BI3: I plan to continue using DW app regularly (mean: 4.0, standard deviation: 1.0, standardized loading: 0.71)
- BI4: I'll probably continue using DW app in the future (mean: 4.0, standard deviation: 0.9, standardized loading: 0.73)

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