Technology Adoption vs. Continuous Usage Intention: do Decision Criteria Change when Using a Technology?

Full paper

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Abstract

Various models in Information Systems (IS) research seek to understand why individuals embrace or resist the adoption or use of a technology. Different models analyze the factors shaping user intentions at different stages of technology adoption and use. Yet, less is known how the factors shaping adoption intention subsequently evolve into continuous usage intention as users become (more) familiar with the technology. This paper investigates participants' (N=549) adoption and continuous usage intention of a smartphone application for energy efficiency twice: at two different stages of experience, but for the same technology, in the same setting, and in particular with the same sample. In both cases, we use the Unified Theory of Acceptance and Use of Technology (UTAUT1&2). While UTAUT explains adoption intention well, we find only moderate support for continuous usage intention. In line with prior research, our data suggests that beliefs are updated from adoption to continuous usage stage.

Keywords

Green IS, UTAUT, adoption intention, continuous usage intention, decision criteria, smartphone applications, energy efficiency

Introduction and Context

IS can inform both management and individual decisions by providing information on a large scale "about causes and effects, and knowledge sharing about what works, what doesn't, and why" (Melville 2010, p. 2). The success or failure of an IS artefact depends on whether consumers resist to use it or are willing to adopt, and to engage with it (Anda and Temmen 2014). IS research has developed various models to understand the factors that drive consumers either to resist a technology (e.g., Kim and Kankanhalli 2009) or to adopt (e.g., Venkatesh et al. 2003) and continuously use it (e.g., Bhattacherjee and Lin 2015). In particular, research on technology acceptance has become one of the most mature domains of IS research (Venkatesh et al. 2012; Williams et al. 2009). Yet, each of the adoption, resistance, or continuous usage models collects a mere snapshot of consumer perspectives at a particular stage of user exposure to a technology. Existing studies have investigated *either* adoption *or* continuous usage behavior – or technology resistance at a particular stage of experience. The results of those snapshots reveal that the barriers and drivers of IS adoption are different from those of continuous usage of a technology (Bhattacherjee and Lin 2015). Yet, relatively little is known about the extent to which the determinants of adoption intention also predict continuous usage of the *same technology in the same setting by the same individuals*.

This article aims to shed light on these questions by evaluating a) adoption intention and b) continuous usage intention of a sustainability smartphone app at two different instances of time: prior and subsequent to the actual usage of the IS. As a theoretical framework, we make use of the two versions of the Unified Theory of Acceptance and Use of Technology – UTAUT1 introduced by (Venkatesh et al. 2003) and its extension UTAUT2 (Venkatesh et al. 2012). While the UTAUT1 has originally been developed to explain adoption intention in an organizational context, its extension UTAUT2 was primarily designed to investigate continuous usage intention on consumer level. We conducted a field study with 637 Dutch households. In the course of the study, the participants had the possibility to use a sustainability smartphone app that visualizes energy and water consumption over time. Prior to the app release, an online survey briefly introduced the basic functionality of the app and collected participants' intention to adopt the smartphone app. A second survey conducted one month after the app release assessed participants' intention to continue using the smartphone app. In both survey waves, participants rated their agreement with statements related to the UTAUT constructs.

Our paper expands current research in three ways: First, we evaluate participants' usage intention at two different stages of experience with the technology: before and after having used it for a month. We apply UTAUT as theoretical framework, as it allows the explanation of both intentions with the same construct. To the best of our knowledge, we are the first scholars to examine both, adoption and continuous usage intention of the same technology in the same setting with the same sample, at least in the domain of green IS. Second, we observe changing patterns in the motivational factors to adopt and continuously use a sustainability app in this context. Third, we collect our data in a large-scale, actual operative setting involving regular users (not a student sample).

Related Work and Research Questions

Most technology acceptance models are based on a simple concept from psychology: beliefs and attitudes about a certain technology largely determine the behavioral intention (BI) to use it, which in turn influences actual usage behavior (Ajzen 1985; Fishbein and Ajzen 1975). IS research distinguishes between adoption intention (first-time usage of an IT innovation) and continuous usage intention (of a previously used and therefore already familiar technology). For both types of intentions, various explanatory models exist. Among the most prominent models, the Technology Acceptance Model (Davis et al. 1989) and the Model of Adoption of Technology in Households (Brown and Venkatesh 2005) predict technology adoption, whereas other theories explain continuous usage intention (Bhattacherjee 2001; Bhattacherjee and Lin 2015; Kim and Malhotra 2005).

Most prior studies have investigated *either* adoption of a new IS *or* continuous usage behavior of a familiar IS, yet the connection between the two intentions and their motivation are less understood. In fact, dynamics of intentions are evaluated by Kim and Malhotra (2005), yet only for dynamic changes within continuous usage intention. Karahanna et al. (1999) use a sample of *potential* users and compare the beliefs affecting their adoption intention with the beliefs affecting usage intention among a (different) sample of *actual* users (early adopters). Yet the study does not reveal whether differences in the importance of those factors are due to individuals updating their beliefs and preferences with experience with the technology or due to differences between the sample of early adopters and the sample of not-so-early/not-yet adopters. So far, we are not aware of studies exploring adoption and continuous usage intention for the same technology at two different stages of experience with the same sample. A model that allows explaining both intentions with same influencing factors is UTAUT: UTAUT1 identifies four determinants of adoption intention, while its extension UTAUT2 explains continuous usage with the help of three additional elements/constructs. Figure 1 visualizes both models (dashed lines for UTAUT1, straight lines for UTAUT2). All constructs are briefly explained in the following:

Behavioral Intention (BI) - BI measures user's self-rated likelihood to perform a particular behavior in the future: the original UTAUT literature measures adoption intention with UTAUT1 and continuous usage intention with UTAUT2. BI is the main predictor of technology usage behavior.

Performance Expectancy (PE) - The first key determinant is PE defined as "the degree to which an individual believes that using the system will help him or her to attain gains in job performance" (Venkatesh et al. 2003, p. 447). PE is positively correlated with BI and usually its strongest predictor.

Effort Expectancy (EE) - The second predictor of technology acceptance is EE defined as "the degree of ease associated with the use of the system" (Venkatesh et al. 2003, p. 450). In other words, EE can be seen as the individual's belief about the effort of learning how to use the new technology. EE is negatively correlated with usage intention.

Social Influence (SI) - The construct SI is defined as "the degree to which an individual perceives that important others believe he or she should use the new system" (Venkatesh et al. 2003, p. 451). The perceived social pressure or the status conveyed from using a technology can considerably manipulate the individual in using a technology: BI increases with a higher SI.

Facilitating Conditions (FC) - The fourth key determinant FC is defined as "the degree to which an individual believes that an organizational and technical infrastructure exists to support use of the system" (Venkatesh et al. 2003, p. 453) and assistance in using the system (assisting supervisor, external help desk, etc.). FC exert a positive influence on BI.

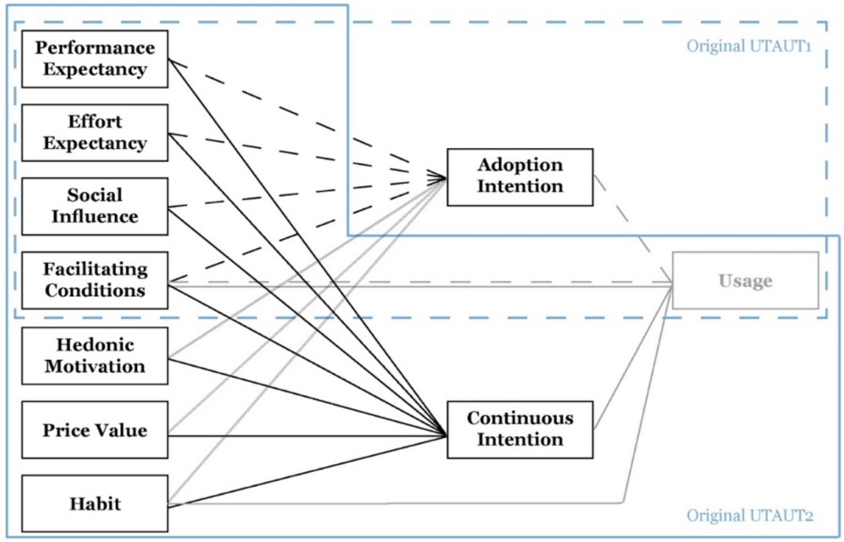

Figure 1: The Unified Theory of Acceptance and Use

Hedonic Motivation (HM) - The first new construct that the UTAUT2 introduces is HM, which is defined as "the fun or pleasure derived from using a technology" (Venkatesh et al. 2012, p. 161). Especially in consumer context the enjoyment of using a technology is crucial, as the individual performs the technology adoption in self-will. Venkatesh et al. (2012) find a strong positive correlation between HM and BI.

Price Value (PV) - The UTAUT2 considers the acquisition costs of technology in the consumer context, as users bear the expenses themselves. Venkatesh et al. (2012) propose the additional key determinant PV defined as the "consumers' cognitive tradeoff between the perceived benefits of the application and the monetary costs for using them" (p. 161) and describe a positive correlation between PV and BI.

Habit (HA) - Another construct presented by the authors of UTAUT2 is habit (HA) defined as "the extent to which people tend to perform behaviors automatically because of learning" (Venkatesh et al. 2012, p. 161). HA can directly influence both BI and usage.

Research Gaps and Research Questions

A brief literature review of existing UTAUT research shows that many studies focus on hypothetical questions explaining the adoption intention of fictive technologies that are not being used later on (e.g., Lai and Lai 2014). Indeed, this approach is useful to validate the measurement scales; yet, it remains unclear to what extent UTAUT constructs predict actual behavior in the long run. Given that existing studies test adoption and continuous usage intention of different technologies in different settings and with different models, a straight comparison of motivational factors is typically not possible. As "IT acceptance and continuance are conceptually and temporally distinct behaviors" (Bhattacherjee and Lin 2015, p. 364) we conjecture that in an early stage of experience with the technology (e.g. when the individual is completely unfamiliar with the technology), other decision criteria are relevant than in later stages of experience shaping the intent to continue using the technology (Arts et al. 2011; Bhattacherjee and Lin 2015; Kim and Malhotra 2005; Premkumar and Bhattacherjee 2008). This leads us to our principal research question:

To what extent do decision criteria for adoption intention differ from those for continuous usage intention at a later stage of experience (for the same individuals)?

When directly comparing the two models for adoption and continuous usage, however, one might argue that differences in the results will obviously arise simply from the fact that two different models are being used. To compare apples with apples, we examine both, adoption intention and continuous usage intention, twice, once using UTAUT1 and once using the UTAUT2. Despite of the fact that both of the intentions are usually tested with one particular version of UTAUT, research practice shows that this boundary is not that strict: While some studies apply UTAUT1 to explain adoption intention (Lai and Lai 2014), others use the model to predict continuous usage intention (Al-Gahtani et al. 2007). Similarly, UTAUT2 is used for both, adoption intention (Oliveira et al. 2014) and continuous usage intention (Lai and Shi 2015).

Therefore, we collect user perceptions of all UTAUT constructs before and after experience with the IS artefact. To the best of our knowledge, no study has been conducted so far that evaluates adoption intention and continuous usage intention of an IS artefact at two instances of time, i.e., for the same technology, in the same setting, and with the same sample. That comparison makes it possible to analyze how the impact of the factors influencing adoption and continuous usage decisions evolves as users gain experience with the IS.

Methodology

In order to answer these research questions, we conducted a large field experiment with 637 Dutch households starting in August 2015. Participating households were recruited in cooperation with a local utility company. The utility company sent out one-page leaflets to customers and employees inviting them to participate in an energy efficiency study. The leaflet informed them that water heating is the second-largest residential energy end use, accounting for 14-18% of the final energy use in households in the U.S. and in Europe (eia 2013; Prognos 2013). The leaflet further explained that study participants would receive for free a smart shower meter that tracks their energy and water consumption in the shower along with a smartphone app. The smart shower meter by itself displayed the current energy and water use during the shower during three months. In the current study, the hardware was for the first time accompanied by a smartphone app that visualizes summary statistics and time trends. During the last month of the study, the participants were invited to use the app to upload the data recorded by the smart shower meter, to access summary statistics, and visualize their energy and water consumption over time (see Appendix 1). Figure 2 gives an overview on the study timeline. In the online survey prior to the study (survey 1), we described the app functionality and collected participants' expectations of the app and their intended and anticipated usage of the app. None of the participants was familiar with the technology when they answered survey 1. Survey 2 (at the end of the three-month study) asked the participants if they had used the app; if that was the case, the survey asked about their beliefs and attitudes towards the app and their intention to continue using the app after the study. The survey questions (see Appendix 2) were based on the scales validated by Venkatesh et al. (2012, 2003) and used 7-point Likert scales. Due to the novelty of both, the smart shower meter and of the accompanying app, for some questions, we had to deviate from the original wording and substitute some items (e.g., "I know how to use this technology") with questions on general dispositions (e.g., "I know how to install apps"). We will return to this point in the analysis of the measurement model.

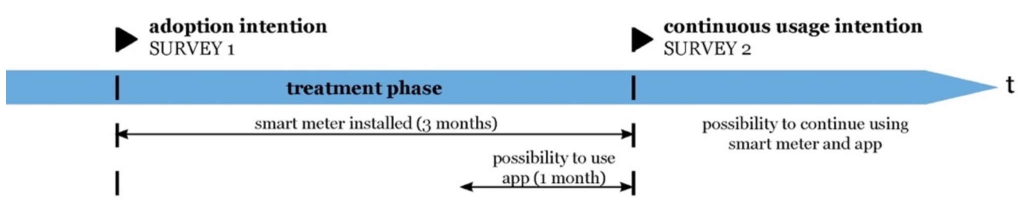

Figure 2: Study timeline

While survey 1 items assessed the UTAUT hypotheses regarding participants' intent to adopt the app, survey 2 items tested the UTAUT hypotheses on participants' intent to continue using the app. As mentioned before, in most cases, UTAUT1 is used to examine adoption and UTAUT2 to assess continued usage of a technology. As we calculate both intentions with both models in order to conduct a thorough comparison, we end up with a 2x2 matrix of analysis: (adoption vs. continuous usage intention) x (UTAUT1 vs. UTAUT2). Overall, we test 22 sub-hypotheses. Hypotheses identifiers in the following paragraphs relate to adoption intention (A) or continuous usage intention (C), UTAUT1 (1) or UTAUT2 (2) and the constructs (PE, EE, etc.). For instance, H.A1PE: ex-ante PE has a positive effect on the adoption intention applying UTAUT1; ...; H.C2HA: ex-post HA has a positive effect on the continuous usage intention applying UTAUT2. Regarding the comparison of ex-ante and ex-post determinants, we further hypothesize that EE and FC weaken with advanced stages of experience: once individuals have started using a technology, they have already made the biggest efforts to familiarize themselves with the technology (H1). Regarding the effects of PE and HM, we expect their importance to increase from adoption intention to continuous usage intention: once individuals have gained some experience with a technology, they will mainly continue using it if they derive added value and enjoyment from it (H2).

Data Analysis and Results

Altogether, we received 637 answers to survey 1 and 538 answers to survey 2. For data analysis, we used Stata/SE 14.0. Two major reasons induced exclusions from the data set: invalid answers and incomplete data (resulting in 549 responses for survey 1 and 486 for survey 2, respectively). When comparing intention of adoption and of continuous usage, we needed to restrict our sample to those participants who had used the app in its full functionality. This left us with 215 participants who had a) filled out both surveys and b) who had used the app. This subset allowed for a fair comparison of adoption intention and continuous usage intention. Obviously, excluding participants who did not use the app could potentially introduce a selection bias. For that reason, we evaluated the model for adoption intention (based on survey 1) twice: once on the full sample of valid responses to survey 1 (N=549) and once only on the subset of app users (N=215). We will return to this point in the discussion of the results presented in Table 2 and Table 3.

UTAUT data is typically analyzed in two separate steps: first, the measurement model tests the data for convergent and discriminant validity to ensure data quality. Second, the structural model analyzes the relationships between the constructs as hypothesized. In the first step regarding the measurement model, we analyzed Cronbach's alpha values to assure reliability of constructs (see Table 2). With values of .6288 and .3345, SI and HA did not meet the recommended threshold of .7 and therefore had to be dropped in the following (Cronbach 1951; Gefen et al. 2000). All other constructs, however, exceeded the reliability threshold and were further examined. In a next step, we tested for convergent and discriminant validity of items. To that end, we conducted a principal component analysis to identify items that statistically belong together and to pooled them to the latent UTAUT constructs.

Table 1 presents cross loadings of items explaining adoption intention in UTAUT2. All items load on the associated components of more than .4, the recommended threshold in IS research (Straub et al. 2004); cross loadings do not exceed this threshold. The Kaiser-Meyer-Olkin index (KMO), which examines whether the data is suitable for this approach at all, reveals a value of .8761. Thus, it scores above the recommended threshold of .5 and can is suitable for principal component analysis (Beavers et al. 2013). The final step of the measurement model tests for discriminant validity. We used Pearson's correlation tests, in which interdependencies between constructs should not exceed .7 (Dormann et al. 2013). The analysis of our data shows acceptable values for all pairwise correlations. Only PE and HM correlate highly ($r=.7803$, $p < .000$); however, as the regression estimation later on will show, multicollinearity issues resulting from this high interdependency do not occur. Conclusively, discriminant validity is assured (the full table cannot be presented here for space constraints and is available upon request).

	1	2	3	4	5	6
PE1	-0.0364	-0.0456	**0.7041**	0.0146	-0.0141	0.0547
PE2	0.0117	0.0457	**0.6832**	-0.0084	0.0308	-0.0634
EE1	0.0251	**0.6566**	0.1210	-0.0218	-0.0256	-0.0840
EE2	-0.0115	**0.7087**	-0.0980	0.0273	0.0013	0.0850
FC1	0.0464	-0.1461	0.0535	0.0075	**0.7347**	0.0354
FC2	-0.0475	0.1641	-0.0510	-0.0087	**0.6766**	-0.0250
HM1	-0.0371	-0.0131	-0.0275	-0.0027	0.0212	**0.8002**
HM2	0.0571	0.0759	0.0693	-0.0081	-0.0241	**0.5722**
PV1	0.0106	0.0673	0.0124	**0.7094**	-0.0036	-0.0706
PV2	-0.0103	-0.0575	-0.0054	**0.7036**	0.0044	0.0641
BI1	**0.7280**	0.0233	-0.0438	-0.0067	0.0037	-0.0252
BI2	**0.6776**	-0.0190	0.0238	0.0089	0.0064	0.0054

Table 1: Cross loadings of items explaining adoption intention in UTAUT2

We carried out the same approach for both intentions in both UTAUT models. Overall, the results pass the recommended thresholds. As mentioned above, to verify whether our smaller sample of actual app users is subject to selection bias, we calculated the model for adoption intention both, on the full sample of 549 households (1st column) and on the smaller sample of 215 app users (2nd column). As Table 2 shows, the regression coefficients are almost identical between the two samples; only a single item, HM2, exhibits a change worth mentioning. The overall model, however, does not change: we can thus infer that our model is robust to the particular sample selection and that the focus on the technology users does not bias the results in any meaningful way. Table 2 presents Cronbach's alpha values, the main loadings of the principal component analysis, and the KMO index (due to space restrictions, cross loadings and pairwise correlations cannot be displayed). Cronbach's alpha values are the same ones in UTAUT1 and UTAUT2. The third column of Table 2 displays the results for continuous usage intention. While the principal component analysis delivers good results for UTAUT1, we find that in UTAUT2, HM items load on the same factors as PE (°) and EE (°°). This is somewhat surprising, given that the same items loaded differently prior to the use of the technology. Overall, all constructs apart from SI and HA pass the measurement model's tests and can be further examined in the structural model. The structural model examines the relationships between constructs.

	ADOPTION INTENTION						CONTINUOUS USAGE INTENTION		
	Main loading in UTAUT1	Main loading in UTAUT2	Cronbach's alpha	Main loading in UTAUT1	Main loading in UTAUT2	Cronbach's alpha	Main loading in UTAUT1	Main loading in UTAUT2	Cronbach's alpha
Sample	Full sample (N=549)			User sample (N=215)			User sample (N=215)		
PE1	0.7420	0.7041	0.8700	0.6985	0.6759	0.8327	0.5993	0.4762°	0.8524
PE2	0.6581	0.6832		0.7144	0.7143		0.7570	0.6888°	
EE1	0.6777	0.6566	0.8621	0.6971	0.7016	0.8335	0.5880	0.8371°	0.7491
EE2	0.7095	0.7087		0.7105	0.7027		0.8019	0.9562°°	
FC1	0.7354	0.7347	0.8729	0.7208	0.7169	0.9455	0.7046	0.6864	0.8541
FC2	0.6758	0.6766		0.6889	0.6914		0.6941	0.7212	
HM1		0.8002	0.8842		0.9410	0.8072		0.4496°	0.8564
HM2		0.5722			0.3230			0.4812°°	
PV1		0.7094	0.8954		0.7049	0.9121		0.6898	0.7791
PV2		0.7036			0.6993			0.7172	
BI1	0.7254	0.7280	0.9556	0.7314	0.7246	0.9427	0.7156	0.7270	0.8441
BI2	0.6853	0.6776		0.6790	0.6600		0.6858	0.6763	
KMO	0.8471	0.8761		0.8188	0.8521		0.6821	0.7855	

Table 2: Measurement model results

In UTAUT context, data analysis techniques of the structural model are diverse and there is no overall unique approach (Gupta et al. 2008). We follow Gupta et al. (2008) in using multiple regressions. Table 3 presents the regression estimation results. For adoption intention as dependent variable, regressions were run on the full sample (1st column) and on the user sample of 215 households (2nd column). Again, we find similar results. Regression results (significances, effect size) are almost identical when including SI and HA (which have failed the measurement model tests) as independent variables in the model.

	ADOPTION INTENTION				CONTINUOUS USAGE INTENTION	
Model	UTAUT1	UTAUT2	UTAUT1	UTAUT2	UTAUT1	UTAUT2
Sample	Full sample (N=549)		User sample (N=215)		User sample (N=215)	
R^2	0.6465	0.6782	0.6218	0.6403	0.2070	0.2249
Performance Expectancy	0.5128761 ***	0.3190237 ***	0.3693373 ***	0.2716530 ***	0.4660757 ***	0.2834603 **
Effort Expectancy	-0.2745986 ***	-0.1896856 ***	-0.2899000 ***	-0.2177455 ***	-0.0195628	0.0646276
Facilitating Conditions	0.2474619 ***	0.2222112 ***	0.3783821 ***	0.3553009 ***	0.0593007	0.0907068
Hedonic Motivation		0.3135260 ***		0.1993817 ***		0.2829456 **
Price Value		0.0097629		0.0114477		0.0159642

Table 3: Structural model results (* p<.1, ** p<.05, *** p<.01)

As the R^2 values show, depending on the model, between 65% and 68% of the variance in the adoption intention can be explained. In UTAUT1 all factors but SI are highly significant (***); in UTAUT2, PE, EE, FC, and HM are highly significant. The explanatory power and effects are robust over the different partitions of the sample and only slightly differ in their dimension (e.g., while the beta coefficient of EE for the full sample is -.18, it is -.21 for the smaller sample.). Overall, both, UTAUT1 and UTAUT2, explain adoption intention to a high degree. In contrast to the good model fit for adoption intention, both models explain a much lower variance in continuous usage intention (with R^2 of 21% and 22%, respectively). In UTAUT1, only PE is (highly) significant, whereas EE and FC fail to be significant predictors of continuous usage intention (even at the 10% level); in UTAUT2, PE and HM are significant. EE and FC do not seem to be relevant in explaining continuous usage intention in either model.

Discussion and Conclusion

Adoption intention - We find strong support for both, UTAUT1 and UTAUT2, to explain consumer intention in the context of adopting a novel sustainability smartphone app. With R^2 values ranging between 65% and 68%, both models explain a high fraction of the variance in adoption intention. This number is considerably higher than the findings in the original papers (~40% in UTAUT1 and ~ 44% in UTAUT2 (Venkatesh et al. 2003, 2012)), in a green IS setting with a modified TAM/UTAUT (~ 48% (Wati and Koo 2012)), and in line with the results of other UTAUT studies in general and in a green IS setting (~ 70% (Gao et al. 2015)). In the green IS context, the explanatory power of the adoption intention in UTAUT1 and UTAUT2 is even stronger than in studies relying on complex combinations of technology acceptance models with additional impact factors such as environmental motivation, pro-environmental values or attitudes introduced for that very context (Wati and Koo, 2012; Wolf and Seebauer, 2014). Regarding the effects of key determinants, our data confirm the hypothesized influence of PE, EE, and FC. In addition, HM significantly determines adoption intention in UTAUT2. We find support for the traditional UTAUT hypotheses H.A1PE, H.A1EE, H.A1FC, H.A2PE, H.A2EE, H. A2FC and H.A2HM. On the other hand, PV does not meet the required significance levels of .05 and H.A2PV is not supported. The lack of a significant impact of PV on adoption intention is probably due to the fact that the technology was provided free of charge in our study setting: in that case, hypothetical questions about fictive prices do not seem to result in meaningful findings. SI and HA did not pass the data quality tests in the measurement model; therefore, the corresponding hypotheses could not be tested. Regarding SI, we conjecture – in particular, in the context of energy conservation – that individuals do not necessarily know what other individuals around them expect them to do or not to do. As (Nolan et al. 2008) show, individuals who change their behavior due to the influence of social norms may not even be aware of that influence. The poor results in data quality tests of HA, on the other hand, may be due to the survey questions: in contexts like ours where none of the participants had previously used the technology, the usual set of HA questions does not make sense. Instead, we asked whether the participants were familiar with similar apps. As this modification did not result in a reliable construct, future research should investigate whether HA should be dropped in models evaluating the adoption of an unknown technology or whether there are reasonable strategies to include a modified version of HA.

Continuous usage intention - Considering the continuous usage intention of our app, the support for both UTAUT models is much lower: only up to 22% of the variance in continuous usage intention can be explained. Overall, we find support for the constructs PE and HM (H.C1PE, H.C2PE and H.C2HM). Other hypotheses relating to the continuous usage intention cannot be tested or supported (at $p<.05$). Regarding SI, PV, and HA, please refer to the comments in the paragraph above. The insignificant impact of EE and FC will be discussed in the following paragraph. As we find only moderate support for explaining continuous usage intention, we encourage to further study continuous usage intentions accordingly to Bhattacherjee (2001) and Bhattacherjee and Lin (2015).

Dynamic perspective of UTAUT determinants – While EE and FC considerably determine adoption intention, their effect on continuous intention is very small and statistically insignificant. This is hardly surprising: if already familiar with a technology, efforts of mastering a technology or availability of the necessary support infrastructure become obsolete (H1 is supported). In contrast, PE and HM significantly determine adoption intention and continuous usage intention. With an increasing experience with the technology, the impact of PE and HM on further usage intention appears to increase. Our hypothesis H2 that individuals only persist using a technology when it delivers added value (PE) and/or brings enjoyment (HM) is thus supported. These results are in line with the findings by Karahanna et al. (1999) who compared the adoption intention of potential users to the continuous usage intention of a sample of actual users. As an additional way to examine the transient behavior of technology usage determinants, we tested whether continuous usage intention can be explained by the ex-ante beliefs about the technology prior to using it. We find that those beliefs only explain 3% of the variance in continuous usage intention. The comparison of the explanatory powers (3% with ex-ante factors vs. 22% with ex-post factors) suggests that expectations and beliefs are being updated with an increasing experience with the technology. Hence, decision criteria cannot be considered a static set of beliefs and attitudes, but they change with an increasing experience with the technology. This is in line with IS continuance scholars (e.g., Bhattacherjee and Lin 2015; Kim and

Malhotra 2005) and with existing literature in marketing which states that decision criteria vary along the adoption process (Arts et al. 2011). We conclude that it makes sense to examine continuous usage intention independent of the consideration of adoption intention.

Our work contributes to existing literature primarily by examining influencing factors of adoption and continuous usage intention of the same technology in the same setting with the same users applying one of the prominent theories in the field, namely UTAUT. We are not only among the first scholars to apply this theory to the field of sustainability, but also work with data collected from *the same sample at two different stages of experience with the technology*, e.g., before and after having used the technology. In that way, we are able to make straight comparisons between the decision criteria at both stages of experience. Our approach of using both UTAUT models in parallel allows us to rule out that differences between the adoption and continuous usage stage merely arise from the fact that two different models were used in those stages.

The results of this study are subject to a number of limitations. First, two versions of the smartphone app were offered (Android and iOS). Even though they were designed as similar as possible, they differ slightly in their usability, which may influence key determinants. Second, our findings are based on a sample of 637 households. While they are probably more representative for the general population than the student samples that many studies resort to, we are still dealing with an opt-in sample from a single country. To what extent our findings can be generalized to society as a whole or to different cultural settings is yet to be determined. Due to space limitations, moderators such as gender or age could not be tested, even though the data was collected. Third, due to the novelty of the technology, some of the traditional UTAUT items (in particular on SI and HA) did not make sense in their original wording. Our newly created items did not pass the quality tests of the measurement model and, hence, relationships could not be tested. These results suggest that these constructs may need an adaption in the context of brand new technologies. Fourth, regarding the generalizability of our study, our findings are based on intentions regarding a particular sustainability smartphone application that was actually used by the participants. Obviously, the (dis)satisfaction with the specific characteristics of that particular app influences participants' continuous usage intention and may bias the results. At the same time, this is the case with any IS; even if a study focuses on a more generic type of technology (e.g., "mobile banking" or "smartphone usage"), the participants probably have very concrete instances of those technologies in mind when answering those questions (e.g., the particular mobile banking software provided by their local bank). Yet the UTAUT model does not provide for these potential sources of distortion. More research with other technologies should be conducted to determine whether our findings apply to other contexts as well.

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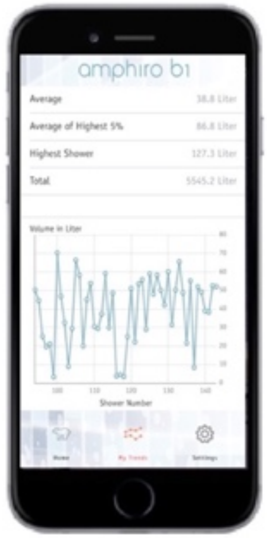
Appendix

Appendix 1: Technology of interest

smart shower meter

Android screenshot



iOS screenshot

Appendix 2: Survey items for adoption intention and continuous usage intention

PE1 I would find (found) such a shower tracking app useful.
PE2 Such an app could help (The app helped) me to keep an eye on my energy and water consumption.
EE1 I think I would understand (I understood) the visualized information provided by the app easily.
EE2 Learning how to use such an app would be (was) easy for me.
SI1 People who have an influence on me think that such an app is a cool innovation.
SI2 People who are important to me think that I should keep an eye on my energy and water consumption in the shower .
FC1 I have a smartphone on which apps can be installed.
FC2 I know how to install apps on my phone.
HM1 Using such an app would be (was) fun.
HM2 I think the information provided by such an app would be (is) interesting.
PV1 Imagine the device and the app would together cost 79,90 EUR. The device and the app would be (are) reasonably priced.
PV2 I could imagine buying the device and the app for 79,90 EUR. (Assuming you did not have the device and the app any more: I could imagine buying the device and the app together for 79,90 EUR.)
HA1 I am currently using apps for tracking my personal activities (running, expenditures, nutrition, etc.).
HA2 I already actively monitor my water and energy consumption (besides this app) [when paying my bills, reading my electricity meter, using a cost control device, etc.].
BI1 I would try out such an app during the time of the study. (I do not intend to use the app during the next few months.)
BI2 If given the possibility, I intend to use such an app several times during the next few months. (I intend to use the app several times during the next few months.)