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SUSTAINABILITY IN PRIVATE HOUSEHOLDS - INVESTIGATING ACCEPTANCE OF SMART ENERGY APPS

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Research Paper

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Abstract

As the use phase of buildings produces a substantial negative environmental impact, mechanisms to guide individuals towards more sustainable energy consumption are of interest. Smart energy apps which constantly monitor energy consumption and provide energy reduction recommendations to private households are a promising tool to tackle this issue. However, as little is known about factors driving their adoption, it remains unclear whether their potential can be leveraged. Against this backdrop, this study derives a technology acceptance model for smart energy apps which builds on a quantitative survey with 300 participants and the partial least squares approach. The results highlight personal innovativeness and environmental norms as additional acceptance factors. Our study points at the importance integrating both individual and technological aspects in technology adoption research, unveils potential levers for IS to drive adoption, and provides guidance to smart energy app designers.

Keywords: Smart energy app, UTAUT 2, Technology acceptance.

1 Introduction

The building sector alone accounts for 36% of European greenhouse gas emissions, making it a key lever for climate action (European Commission, 2018). Its dominant share of emissions occurs during the actual use phase (Khasreen, Banfill and Menzies, 2009): Energy consumption patterns in private households, such as heating or washing behaviour (Santamouris and Vasilakopoulou, 2021). Hence, when changing the building sector, developing mechanisms to foster climate-friendly energy use behaviour in individuals is a good starting point (Santamouris and Vasilakopoulou, 2021). However, individuals' energy consumption is highly habitual and thus tricky to change (Pongiglione, 2011; Verplanken and Whitmarsh, 2021). As a first step, individuals must develop awareness of their energy consumption and possibilities for improvements (Vainio *et al.*, 2019). Information systems (IS) have the potential to aid this awareness process as they can enable information access and transparency. In the context of energy consumption in private households, smart energy apps are best suited for creating this awareness and guiding behaviour, because mobile phones are easy to transport and already widespread across populations (Attour *et al.*, 2020). We understand smart energy apps as mobile applications that integrate functionality for constantly monitoring energy consumption in private households and for providing recommendations on energy reduction potential – both of which are features proven to reduce energy consumption (Wilhite and Ling, 1995; Alaa *et al.*, 2017; Attour *et al.*, 2020).

Current research on smart energy apps has provided valuable insights on both technical ways to provide individuals with the right information to improve energy consumption behaviour (Fischer, 2008; Li *et al.*, 2021), as well as analyses on the effectiveness of such digital technology (Burchell, Rettie and

Roberts, 2016; Nikou, 2019; Berger, Greinacher and Wolf, 2022). With the knowledge that smart energy apps are suitable for fostering climate neutrality in the building sector, the next critical step is to drive their adoption (Attour *et al.*, 2020; Yew, Molla and Cooper, 2022). No positive environmental effect can be materialized if these apps are helpful in theory but not adopted and used in real-life (Lee, Rhee and Dunham, 2009; Petter, DeLone and McLean, 2013). As a result, technology acceptance research is wide-spread in the IS community, raising the question of how adoption antecedents might differ for smart energy apps as compared to other mobile applications (Mehrtens, Cragg and Mills, 2001; Beck *et al.*, 2008; Tamilmani *et al.*, 2021). Up until now, most adoption research has focused on either IS with involuntary implementation (i.e., IS in the workplace), on firm- or group-level adoption, or on voluntarily used apps that offer a high entertainment potential to users (e.g., Ashraf *et al.*, 2019; Maier *et al.*, 2022). In the context of smart energy apps, its neither of the three because these apps are voluntary, but energy consumption and associated activities (e.g., washing, cleaning, etc.) are not associated with any hedonic motivation. Rather, the context is defined by high levels of habitual integration in one's everyday life, complemented by complex IS infrastructure (i.e., combination of the app itself, measuring infrastructure, smart household appliances) and diverse stakeholders (i.e., houseowners, housing associations, public institutions, energy providers), making smart energy apps a niche technology type.

The two existing studies on smart energy app adoption have generated valuable insights: On top of the widely established adoption antecedents from models such UTAUT or the theory of planned behaviour (Fishbein M. and Azjen I., 1975; Venkatesh, Thong and Xu, 2012), Yew et al. (2022) identified environmental altruism and exposure to sustainability information, as well as demographic and household characteristics such as the number of children and the apartment size as important factors. In addition, Attour et al. (2020) demonstrate that technical characteristics are mainly driving adoption decisions, while individual characteristics (e.g., privacy concerns) drive the frequency of utilization. As in many IS domains, the focus of existing research has been a technology-centric one, bearing the risk of a "technology fallacy" and thus the neglection of important social factors (Kane, 2019). Other contexts have proven that context-sensitive individual characteristics and personality traits are a critical antecedent to technology adoption, making an understanding of the related factors indispensable (He and Veronesi, 2017). However, as technology adoption occurs in socio-technical systems, neither a pure focus on technical nor on individual characteristics is expedient (Lyytinen and Newman, 2008). Given the current lack of focus on individual characteristics, we propose the following research question: *What adoption model adequately integrates a stronger focus on individual factors with existing perspectives on individuals' intention to adopt a smart energy app?*

To answer the research question, we propose a theory-backed research model of technology acceptance for smart energy apps, which builds on the rich theories of technology acceptance in IS research (Venkatesh, Thong and Xu, 2012; Girod, Mayer and Nägele, 2017). We test the model by way of a structural equation model using data from 300 individuals. We find that on top of established variables, personal innovativeness and environmental norms are important factors impacting behavioural intentions to use smart energy apps, while technological aspects such as privacy concerns or digital literacy were less relevant in our context. Overall, our study contributes to existing research by expanding prior adoption models with the importance of personality traits and individual beliefs and by unveiling potential levers for IS to drive adoption, such as more transparency and information availability. In addition, we provide guidance to smart energy app designers by demonstrating the importance to incorporate incentives addressing environmental benefits of the app or the innovativeness of users in order to drive adoption.

2 Theoretical background

2.1 Energy saving potential in private households

One of the main drivers of CO_2 emissions is the energy consumption of private households (Burchell, Rettie and Roberts, 2016; Fenner *et al.*, 2018). As a result, research has investigated potential intervention strategies for fostering pro-environmental choices. IS have been proven a suitable tool to scale up these intervention strategies, as they can automatically process consumption data and enable large-scale and cost-effective consumer engagement (Loock, Staake and Thiesse, 2013; Majumder *et al.*, 2022). The increasing usage of smart home technology makes interventions based on smart energy services possible (Paukstadt, 2019; Berger, Greinacher and Wolf, 2022). Usually, tenants can access and control such systems via a touchscreen panel, a voice assistant, or a smartphone app (Herrero, 2018). The combination of smart meters, variable electricity tariffs, and domestic appliances provide households with the potential to improve energy efficiency and lower consumption. Smart energy apps enable consumers to actively connect to and control various household devices. They allow tracking and comparing one's energy consumption (Berger, Greinacher and Wolf, 2022) and make it possible to give users feedback (Paukstadt, 2019), creating the necessary transparency about consumption patterns (Weiss *et al.*, 2009). Smart energy apps for households include many functionalities, such as visualizing and contextualizing energy consumption, providing saving tips and recommendations on how to use specific appliances more sustainably, as well as giving users the possibility to benchmark their energy consumption with others (Attour *et al.*, 2020; Yew, Molla and Cooper, 2022).

Such disclosure of information has been researched as a promising tool for guiding individuals toward more sustainable choices (Burchell, Rettie and Roberts, 2016; Sunstein, 2019). Especially in the case of private households, real-time information is effective (Paukstadt, 2019). However, as energy is an invisible resource that is only consumed indirectly, many householders cannot assess the importance of its consumption (Fischer, 2008). The respective units of measurement are difficult to grasp, and people struggle to relate them to their real-life energy consumption. The feedback currently available on energy consumption often lacks salience, leaving untapped potential.

2.2 Smart energy apps and technology acceptance

Smart energy apps pose a promising chance for nudging individuals towards more sustainable living. However, the positive effects of these apps only materialize if the technology is actually used and accepted among tenants (Petter, DeLone and McLean, 2013). Individuals' acceptance and rejection of information technology (IT) is a heavily researched field in the IS domain, which is caused by the increased application of new technologies in organizations and society, as well as the continued high failure rate of IS (Tamilmani, Rana and Dwivedi, 2019). As a consequence, examining the factors affecting technology acceptance – in our case, of a smart energy app - helps design technology more purposefully and with a higher fit to users' needs. In the following, we briefly expand on the different general theories existing in technology acceptance research an outline previous adoption research on smart energy apps. The theory of reasoned action (TRA) in the field of social psychology formed the basis for the later developed models of technology acceptance (Fishbein M. and Azjen I., 1975; Venkatesh *et al.*, 2003). Building on the TRA, TAM, the technology acceptance model, is one of the earlier theories in the IS field and has been widely made use of in studies (Davis, 1989). The model is tailored to the IS context and designed to predict the usage and information technology acceptance in an organizational context (Davis, 1989). The model was later extended (TAM 2) with the variable subjective norm in the case of a mandatory setting of IT use (Venkatesh and Davis, 2000). Another model based on the TRA in the context of technology is the theory of planned behaviour (TPB) (Ajzen, 1991). Perceived behavioural control focuses on the belief that behavioural intentions are influenced by the perception of a specific outcome. These models have been criticized to lack general insight into work-technology environments. The Unified theory of acceptance and technology use (UTAUT) addresses these shortcomings (Venkatesh *et al.*, 2003). This theory examines the acceptance of technology among employees. The four variables performance expectancy, effort expectancy, social influence, and facilitating conditions highlight the focus on usage, besides intention, as a predictor of a specific behaviour (Venkatesh *et al.*, 2003). As this theory does not take the psychological or cognitive states affecting intentions into consideration, the model was revised and extended: UTAUT 2 focuses on consumer technologies. The variables of hedonic motivation, price, and behavioural intention characterize the new theory (Venkatesh, Thong and Xu, 2012).

UTAUT 2 has been contextualized in different areas. It applies to, for example, the health sector, by investigating the acceptance of mobile health applications (Schomakers, Lidynia and Ziefle, 2019) or the context of mobile banking (Owusu Kwateng, Osei Atiemo and Appiah, 2019). Girod, Mayer and Nägele's (2017) investigate the relation of personality-specific constructs, besides the well-established economic and technological constructs in the framework of UTAUT 2 and green technologies. In the context of smart homes and smart energy apps, the application is directly embedded into individuals' routines (Aldossari and Sidorova, 2020). The smart energy app focuses on the energy consumption of households and gives individuals tailored feedback and tips on how to improve sustainability. UTAUT 2, with its applicability in consumer technologies and focus on intrinsic motivation is, therefore, a suiting theory for accessing potential users' technology acceptance (Tamilmani, Rana and Dwivedi, 2019). In terms of the adoption of smart energy apps in particular, to the best of our knowledge, only two studies have previously investigated this phenomenon. First, Attour et al. (2020) investigate the adoption of what they refer to as smart energy tracking apps among French residents. Methodologically, their study does not build on the fundamental theories of technology adoption in IS research but rather the innovation diffusion theory (Rogers, 2003). Their findings reveal that the general decision to adopt smart energy apps is driven mainly by characteristics of the respective city itself (e.g., the exact location or demographic variables). In addition, they assess the frequency of use, which was proven to be impacted by the individual characteristics such as privacy concerns or perceived benefits. Yew et al. (2022) on the hand build on the above mentioned TPB and conducted a quantitative survey with citizens in Singapore. Their results highlight the important role of sustainability information availability and environmental altruism as antecedents to social norms. Further, as Attour et al. (2020) they find city and household characteristics like apartment size or the number of children as important drivers of adoption (i.e., as antecedents to perceived control). Both studies present valuable knowledge to foster smart energy app adoption and point at relevant technological and demographic factors. To complement their findings, our research deep dives on a stronger focus on individual characteristics and its integration into existing adoption models.

2.3 Model development and hypotheses

The dependent variable and core construct of our research model is the behavioural intention, which we understand as the individuals' commitment to use and continue to use a technology (Venkatesh, Thong and Xu, 2012). UTAUT 2 also includes the actual use behaviour as a subsequent step in the model. However, this variable cannot be assessed in our context, as smart energy apps are still in experimental stages and not yet established in practice. Therefore, we assess factors influencing the behavioural intention to use a smart energy app as an antecedent to use behaviour. Overall, the adoption of smart energy apps induces a change to the users' daily lives and portrays a part of the overall digitalization of individual lives. However, the adoption of new digital technologies is not only a technological change, but a change to both technical and social factors. Therein, the IS community has interpreted IS change as a change to a socio-technical system, where too often the social part has been neglected (Lyytinen and Newman, 2008). To avoid a technology-bias and integrate the social components in our research model equally, we combine UTAUT 2 with Girod, Mayer and Nägele's (2017) model based on subjective beliefs. Girod et al. (2017) have integrated existing theories on socio-technical systems by developing an adoption model purposefully differentiating personality-specific and technology-specific beliefs in the context of green technologies. Therein, personal beliefs "describe how people perceive themselves, complementing and otherwise mere technology-focused perspective" (Girod, Mayer and Nägele, 2017, p. 417). On the contrary, technology-specific beliefs refer to the idea that a decision is objective and rational, and determined by measures of technology (Girod, Mayer and Nägele, 2017).

The relevant technology-specific variables in UTAUT 2 are *performance expectancy*, *effort expectancy*, f*acilitating conditions*, and *social influence*. As the smart energy app itself will be free of charge, the variable *price* from UTAUT 2 is not included. However, as the functionality of the app also requires certain infrastructure components such as a smartphone, smart meters or smart household appliances, the variable "facilitating conditions" specifically asks, if these requirements are fulfilled. *Habit* is also left out in our study, as this construct cannot be evaluated without the app being in use yet (Venkatesh, Thong and Xu, 2012, p. 161). All four remaining variables (i.e., performance expectancy, effort expectancy, facilitating conditions, and social influence) have been tested as important factors of technology adoption in many different contexts (e.g., Owusu Kwateng, Osei Atiemo and Appiah, 2019; Tamilmani *et al.*, 2021; Venkatesh, Thong and Xu, 2012). Therefore, we do not explicitly hypothesize their effect or put them in focus within our research, but rather focus on novel aspects. However, to increase model validity and not create an omitted variable problem, we include the constructs in the statistical analyses nevertheless (Radaelli and Wagemann, 2019), but discuss the novel results only.

In addition to the original assumptions of UTAUT 2, smart energy apps are marked by the high technological complexity of the different digital technologies interacting (e.g., sensors, algorithms, apps, smart machines), as well as high data input requirements for such apps to function properly. As a result, two additional variables deem central in assessing technology acceptance. Digital literacy describes “the ability to access, search, evaluate modify and distribute digital media and develop skills in the use of new technologies” (Mohammadyari and Singh, 2015, p. 12). The variable deems relevant in the context of smart energy apps, as they are not just exclusively based on a simple interaction between the app and the user, such as reading information. Rather, smart energy apps require the users to set consumption thresholds and improvement goals and participate in rankings among other users. Users that score low on digital literacy often struggle with the usage of digital technologies and may therefore be less engaged in it (Greene, Yu and Copeland, 2014). Following, we investigate the impact of digital literacy on the behavioural intention to use a smart energy app for households and hypothesize:

H1: Higher Digital Literacy leads to higher behavioural intention.

Technical abilities alone are not sufficient to create high behavioural intentions. Due to strong debates about data privacy in the context of internet communication technology (ICT), the topic of data privacy and related concerns emerged. Data privacy can be described as the right to control information and data about oneself (Schomakers, Lidynia and Ziefle, 2019). With the integration of collecting and sharing data into our everyday life through the IoT, privacy concerns arise among users of ICT (Schomakers, Lidynia and Ziefle, 2019). As smart energy apps build on highly sensitive data such as energy usage and heating behaviour, concerns about data security can drastically impact behavioural intentions (Attour *et al.*, 2020). People who perceive the data privacy of such apps as higher will therefore be more likely to trust the system and be more interested in engaging with the app.

H2: Higher Perceived Data Privacy leads to higher behavioural intention.

Girod, Mayer and Nägele (2017) state that technology-specific beliefs are also influenced by personal-specific beliefs. *Hedonic motivation*, adapted from UTAUT 2, is a subjective measure and can therefore be accessed as a personality-specific belief. It describes “the fun or pleasure derived from using a technology” (Venkatesh, Thong and Xu, 2012, p. 161). The positive experience people may connect with the usage of a smart energy app, might impact their behavioural intention. An encouraging experience can be created by for example positive feedback, nudging with gamification elements, and benchmarking against other users, resulting in enhanced enjoyment levels. Deriving pleasure from the usage of a smart energy app may therefore increase the users' behavioural intention to use the application (Aldossari and Sidorova, 2020). This correlation will be investigated by the following hypothesis.

H3: Higher Hedonic Motivation leads to higher behavioural intention.

In the context of general green consumer technologies, the two variables *environmental norm* and *personal innovativeness* were particularly important (Girod, Mayer and Nägele, 2017). Environmental norms can be defined as “the belief that one should act in keeping with the environment” (Girod, Mayer and Nägele, 2017, p. 417). It can positively impact the behavioural intention to make use of green technologies. With smart energy apps as a form of green consumer technologies, consumers have the potential to act upon their subjective values of environmentalism and sustainability. The opportunity of smart energy apps to foster environmentally friendly behaviour will thus increase behavioural intentions. In addition, research on smart energy apps has yielded first insights that personality traits might be of relevance (Yew, Molla and Cooper, 2022). Personal innovativeness complements environmental norm and is described as "the willingness of an individual to try out any new technology" (Agarwal and Prasad, 1998, p. 206). This is based on the concept that people who can be described as innovative in the field of information technology are likely to develop a more positive attitude towards the targeted technology (Lewis, Agarwal and Sambamurthy, 2003). Especially given that smart energy apps are not yet established in households, people with high levels of personal innovativeness will be interested in trying out a new type of app. Investigating whether users' environmental norms and personal innovativeness lead to higher behavioural intention, we hypothesize:

H4: Higher Environmental Norm leads to higher behavioural intention.

H5: Higher Personal Innovativeness leads to higher behavioural intention.

So far, the constructs presented are predominantly static in respect to current political situations. However, with Russia's current war of aggression on Ukraine, a new dimension of energy-saving interest becomes apparent. Global political situations have the potential to strongly impact energy availability and prices. In turn, the local energy consumption decisions can also affect which political regimes are supported through energy trade. Therein, political interest as a construct can affect individuals' desire to change their energy consumption behaviour and consequently use the smart energy app (Chen, Xu and Arpan, 2017). There can be found a consistent correlation between affiliation for different political parties and environmental concerns (Chen, Xu and Arpan, 2017), as well as interest in energy savings (Rohde *et al.*, 2012). In the context of a smart energy app that focuses on supporting people to consume energy more sustainably, political interest is hence a relevant variable to access. Our hypothesis reads:

H6: Higher Political Interest leads to higher behavioural intention.

An overview of all hypotheses in the research model is presented in Figure 1 below.

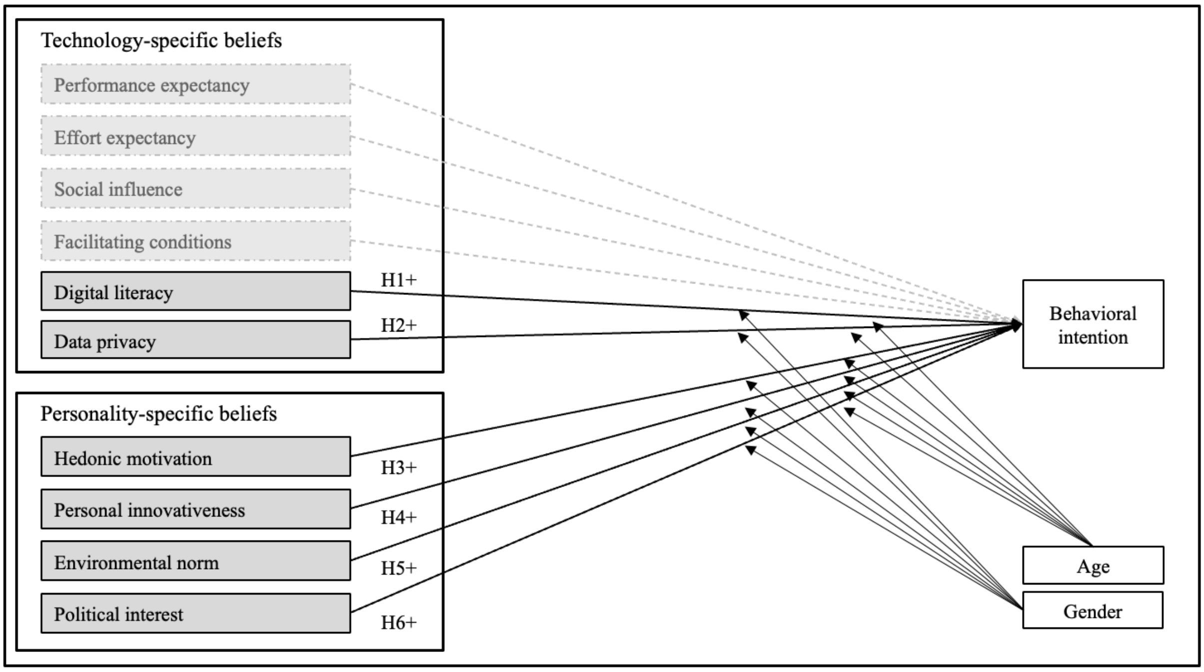

Figure 1. Research model based on UTAUT 2 and the model of subjective beliefs (Girod, Mayer and Nägele, 2017; Venkatesh, Thong and Xu, 2012).

3 Method

3.1 Data collection

In order to test our research model and the respective hypotheses, we conducted an online survey. Participants were recruited via the digital panel provider “Prolific”, as panel providers have been proven a suitable tool for survey recruiting in IS research (Lowry *et al.*, 2016; Weiler *et al.*, 2022). The data collection process lasted from 23.09.2022 - 24.09.2022 and a total of 300 completed responses was gathered. The survey was open to participants residing in Germany, as all parts of the questionnaire were in German language. Additionally, the panel provider ensured a 1:1 ratio of male and female participants. Following the recommendations of Curran (2016), we included two attention checks as validity indicators to identify any survey participants that might be bots or highly inattentive. The German living situation is characterized by 56% of the population living in an apartment and 27% in a one-family house. 58% rent their home (Statista Research Department, 2022). Each household is equipped with its own electricity meter and can choose its energy provider. The biggest share of energy consumption of most households is based on gas. 55% of this gas is imported from Russia (Bundeszentrale für politische Bildung, 2022). With the backdrop of the war in Ukraine, gas imports from Russia decreased drastically and energy prices increased massively over the past months (Statista Research Department, 2023). As a consequence, German households in particular are very encouraged to save energy, making the German context a promising context for the proposed study.

Smart energy apps are currently not commonly used in private households. Therefore, we needed to introduce survey participants to features of such an app. We made use of an application currently under development in a research project on smart and sustainable districts. The survey started off with a detailed description and several screenshots of this app, to establish a shared understanding of the technology. We provided survey participants with information about the different functionalities of the app, such as energy saving tips, a transparent description of energy consumption, and push notification when sustainable energy is on the market. Through screenshots of the user interface, we visualized these technical features and tools. The survey consisted of 36 questions covering all variables and constructs in our research model. To ensure research quality and validity, all constructs were based on and adapted from scales that had previously been validated in peer-reviewed research. A priori measures like anonymity of the participants, informing participants that there is no true or false answer, carefully scaling and wording developed items and asking for honesty, were taken to prevent common method bias (Podsakoff *et al.*, 2003). The final questionnaire items and their source are summarized in Table 1. Smartphones are used in the project setting as the carrier technology of the smart energy app.

Behavioural Intention (BI) (Venkatesh, Thong and Xu, 2012)	BI1 BI2 BI3	I intend to continue using the application in the future. I will always try to use the application in my daily life. I plan to continue to use the application frequently.
Performance Expectancy (PE) (Venkatesh, Thong and Xu, 2012)	PE1 PE2 PE3 PE4	I find the application useful in my daily life. Using the application increases my chances of achieving things that are important to me. Using the application helps me accomplish things more quickly. Using the application increases my productivity.
Effort Expectancy (EE) (Venkatesh *et al.*, 2003)	EE1 EE2 EE3 EE4	My interaction with the application would be clear and understandable. It would be easy for me to become skilful at using the application. I would find the application easy to use. Learning to operate the system is easy for me.
Social Influence (SI) (Venkatesh *et al.*, 2003)	SI1 SI2 SI3	People who are important to me think I should use the application. People who influence my behaviour think I should use the application. Having the application is a status symbol

Facilitating Conditions (FC) (Venkatesh *et al.*, 2003; Venkatesh, Thong and Xu, 2012)	FC1 FC2 FC3 FC4	I have the resources necessary to use the application (e.g., a smartphone). I can get help from others when I have difficulties using the application. The application is not compatible with other systems I use (e.g., smart washing machine). Using the system fits into my work style (e.g., home office).
Data Privacy (DP) (Abrahão, Moriguchi and Andrade, 2016; Chen, Xu and Arpan, 2017)	DP1 DP2 DP3	The risk of an unauthorized party misusing app data is low. The risk of an unauthorized party misusing personal information from the application is low. The risk of an unauthorized party misusing personal information from the application is low.
Digital Literacy (DL) (Venkatesh *et al.*, 2003)	DL1 DL2	I have the knowledge necessary to use the application. It takes too long to learn how to use the application to make it worth the effort.
Hedonic Motivation (HM) (Venkatesh, Thong and Xu, 2012)	HM1 HM2 HM3	Using the application is fun. Using the application is enjoyable. Using the application is very entertaining.
Environmental Norm (EN) (Girod, Mayer and Nägele, 2017)	EN1 EN2 EN3	I have a bad conscience when energy is wasted in the household. I feel personally obliged to avoid unnecessary energy consumption wherever possible. I personally feel that it is important to think about the environment in my everyday behaviour.
Personal Innovativeness (PI) (Girod, Mayer and Nägele, 2017)	PI1 PI2 PI3	Among my peers, I am usually the first to explore new applications. If I heard about a new application, I would look for ways to experience it. I like to purchase new, innovative applications
Political Interest (PolI) (Sindermann, Kannen and Montag, 2022)	Pol1 Pol2	How interested are you in politics in general? How much time do you spend catching up on global news?

Table 1. Survey items.

3.2 Data analysis

The relationships hypothesized in our research model represent a cause-effect model embedded in the theoretical foundations of the technology acceptance theory UTAUT 2 (Venkatesh, Thong and Xu, 2012). Given the high number of hypotheses and thus the high model complexity, we apply partial least squares (PLS) structural equation modelling to test our model (Nunnally and Bernstein, 1994). PLS is well established in IS research and allows for validating the effects presented in section 2 (Cheng, 2011; Ray, Kim and Morris, 2012; Diel, Höger and Schick, 2021). In order to derive meaningful insights from our study, we followed a dyadic approach: we first tested and demonstrated both the reliability and validity of all constructs included in the questionnaire (latent variables) before quantifying the proposed structural model. We assessed convergent validity through factor loadings, composite reliability, and average variance extracted (AVE) for the validity testing of the different constructs. Established minimal thresholds for factor loadings are 0.7, respectively 0.4 (Hair, 2014), for composite reliabilities 0.8, and 0.5 for AVE (Fornell and Larcker, 1981; Nunnally and Bernstein, 1994). To also account for the internal consistency of the variables, we computed Cronbach's α with a minimum threshold of 0.7 (Campbell and Fiske, 1959). As the last step in ensuring the validity of our constructs, we analysed discriminant validity (Campbell and Fiske, 1959). Therein, we 1) assessed whether the square root of the AVEs previously computed is greater than the off-diagonal inter-construct relation (Fornell and Larcker, 1981), and 2), checked whether the heterotrait-monotrait (HTMT) criterion of Henseler *et al.* (2015) of all constructs is below 0.85. For model testing and quantification in the second phase, we applied the PLS algorithm and set the number of bootstraps to 5000. We considered the standardized path coefficients between constructs and their respective p-value. On an operative level, we used the 'SmartPLS 4' statistical software for all analyses and parameter estimation.

4 Results

The survey was completed by 300 participants total with an average completion time of 6.1 minutes. As no participants failed the attention checks, all data sets were included for analyses. Of all participants, 146 are female, 150 are male, and 4 identify as diverse. With respect to the age distributions, participants ranged from 18-71 years old, with a mean age of 35 years, and a standard deviation of 10.55 years. In terms of the highest education degree received, 33.7% of the participants hold a high school diploma, 24.7% a bachelor’s degree, 27.7% a master’s degree and of 1.67% a PhD.

As the constructs in our research model are latent variables, we ensure reliability and validity through different analyses. We make use of factor loadings, composite reliability, and average variance extracted (AVE) – all of which are established statistical procedures for conducting PLS. Additionally, we considered Cronbach’s α to analyse the internal consistency of the constructs (Table 2). Looking at the test results initially, the factor loadings of the originally considered items PE4, FC1, FC2, DP3 and SI3 are below the recommended threshold (between 0.4 and 0.7) and the deletion of these items improves the AVE and composite reliability. We thus removed these items from the model to improve the validity (Hair, 2014). Question DL1 also has low loadings, but as the deletion does not improve the AVE and composite reliability, we retain the indicator (Hair, 2014). As illustrated in Table 1., almost all other constructs and items meet the recommended thresholds. Exceptions are facilitating conditions and digital literacy, which did not meet Cronbach’s α and the composite reliability recommendations. But as these variables are salient to the context of the research model and values are very close to the recommended threshold of composite reliability, we do not exclude them from further analysis.

In addition, we test for discriminant validity, which is describes the “extent to which a construct is truly distinct from other constructs by empirical standards” (Hair, 2014, p. 104). It can be analysed via the Fornell-Larcker criterion, by examining if the latent variable correlation is smaller than the square root of the AVE values, as illustrated in Table 3. As an additional measurement, we refer to the heterotrait-monotrait (HTMT) criterion of Henseler *et al.* (2015)**,** assuring that all values are below 0.85 (Table 4). Given the single-method approach, we examine common method bias post hoc with the correlated marker variable technique. As the significance of the correlations was not influenced, no common method bias is present in our study (Lindell and Whitney, 2001; Craighead *et al.*, 2011). Additionally, the variance inflation factor (VIF) of all variables is below 3.3 (which represents the absence of collinearity and common method bias) (Kock, 2015) and Harman’s single factor test verified that no common method bias is present, as the highest total variance extracted by one factor was 23,4% (Podsakoff *et al.*, 2003; Craighead *et al.*, 2011). Tables 1, 3 and 4 do not (or only partly) include the dependent variable BI, as the calculations cannot be carried out for the dependent variable. Variables are greyed out, because they have been tested as important factors in different contexts of technology acceptance before and are therefore not the focus of our hypotheses.

		Internal reliability		**Convergent and discriminant validity**		
Construct	**Item**	**Cronbach’s alpha**	**Factor loading**	**Composite reliability**	**AVE**	**VIF**
Behavioural Intention (BI)	BI1 BI2 BI3		0.969 0.889 0.920			
Performance Expectancy (PE)	PE1 PE2 PE3	0.887	0.891 0.918 0.898	0.929	0.815	1.735
Effort Expectancy (EE)	EE1 EE2 EE3 EE4	0.895	0.839 0.897 0.877 0.872	0.926	0.759	1.517

Social Influence (SI)	SI1 SI2	0.919	0.960 0.963	0.961	0.925	1.374
Facilitating Conditions (FC)	FC3 FC4	0.425	0.783 0.810	0.776	0.635	1.283
Data Privacy (DP)	DP1 DP2	0.903	0.962 0.947	0.935	0.911	1.179
Digital Literacy (DL)	DL1 DL2	0.595	0.496 0.997	0.745	0.620	1.339
Hedonic Motivation (HM)	HM1 HM2 HM3	0.866	0.910 0.881 0.873	0.918	0.789	1.691
Environmental Norm (EN)	EN1 EN2 EN3	0.835	0.870 0.902 0.822	0.899	0.749	1.061
Personal Innovativeness (PI)	PI1 PI2 PI3	0.825	0.859 0.894 0.829	0.896	0.741	1.360
Political Interest (PolI)	Pol1 Pol2	0.779	0.914 0.896	0.900	0.819	1.077

Table 2. Internal reliability and convergent validity of the measurements.

	PE	EE	SI	FC	**DP**	**DL**	**HM**	**EN**	**PI**	**PolI**
PE	**0.903**									
EE	0.424	**0.871**								
SI	0.390	0.304	**0.962**							
FC	0.205	0.184	0.278	**0.797**						
DP	0.279	0.069	0.293	0.136	**0.954**					
DL	0.277	0.455	0.132	0.028	-0.062	**0.787**				
HM	0.566	0.339	0.397	0.279	0.227	0.235	**0.888**			
EN	0.157	0.168	0.103	0.094	0.068	0.098	0.119	**0.865**		
PI	0.240	0.174	0.287	0.419	0.181	0.038	0.356	0.041	**0.861**	
PolI	0.094	0.092	0.070	0.120	-0.019	0.137	0.145	0.145	0.172	**0.905**

Table 3. Fornell-Larcker criterion (elements on the diagonal are square roots of the AVE).

	PE	EE	SI	FC	**DP**	**DL**	**HM**	**EN**	**PI**	**PolI**
PE										
EE	0.473									
SI	0.433	0.336								
FC	0.327	0.298	0.442							
DP	0.311	0.079	0.319	0.214						
DL	0.456	0.825	0.216	0.287	0.056					
HM	0.639	0.380	0.444	0.457	0.253	0.235				
EN	0.184	0.187	0.122	0.277	0.078	0.166	0.137			
PI	0.277	0.204	0.328	0.708	0.209	0.088	0.420	0.075		
PolI	0.111	0.113	0.082	0.206	0.042	0.237	0.179	0.173	0.127	

Table 4. HTMT.

After ensuring the reliability and validity of all constructs, we proceed with the evaluation of our research hypotheses, conducting a PLS. In total, the variables in the research model explain 50% (R^2=0.50) of the variation of the dependent variable behavioural intention. Analysing the path coefficients and the p-value of all constructs, the bootstrapping procedure yielded the results in Table 5. As indicated, personal innovativeness (H4, β=.172, *P*<.01) and environmental norm (H5, β=.105, *P*<.01) significantly influence behavioural intention. Surprisingly we found no direct relationship between behavioural intention and the variables data privacy (H2, β=.034, P=.488), digital literacy (H1, β=.074, *P*=.303), hedonic motivation (H3, β=.0.085, *P*=.158), and political interest (H6, β=.020, *P* =.671).

Further we investigated the role of the moderators age and gender with the bootstrapping procedure. The diverse gender could not be investigated, because the sample size of four diverse participants is too small for statistical procedures. The moderator gender impacts the effect of the independent variables on behavioural intention. The behavioural intention to use a smart energy app, is 5.4% higher for men, than for women. Regarding the two significant variables, for environmental norm (m: H5, β=.139, P =.019; f: H5, β=.075, P =.303), the effect is stronger an only significant for male participants. Whereas personal innovativeness is higher and significant in the case of female participants (m: H4, β=.126, P =.127; f: H4, β=.203, P =.002). Looking at the moderator age we divided the participants into the age groups 18-24, 25-29, 30-34, 35-39, 40-49, and 50-71. The intention to use explained by the research model increases with age, and peaks at the age group 30-34, with an average intention to use of 3.3 (out of 5). In the age group 40-49 the intention to use decreases to the lowest overall score of 2.8 and increases again in the age group 50-71 to 3.2. Regarding the variables, no moderation effects are tested significant in the age groups 40-49 and 49-71. The impact of personal innovativeness is significantly stronger in the age group 30-34 (H4, β=.389, P =.046). The environmental norm is not impacted by the age.

	Path coefficient β	**P-values**		**Hypotheses**	
DL	0.074	0.303	n.s.	H1 +: DL→BI	*Rejected*
DP	0.034	0.488	n.s.	H2 +: DP→BI	*Rejected*
HM	0.085	0.158	n.s.	H3 +: HM→BI	*Rejected*
PI	0.172	0.001	**	H4 +: PI→BI	*Accepted*
EN	0.105	0.007	**	H5 +: EN→BI	*Accepted*
PolI	-0.020	0.671	n.s.	H6 +: PolI→BI	*Rejected*

(p-values: n.s. = not significant, * < 0.05, ** < 0.01, *** < 0.001)

Table 5. PLS results, assessment of hypotheses.

In addition to the proposed research model, we included two explorative open-text questions in the survey to foster the interpretation of the quantitative results and spark ideas for future research in this field. While these questions are not suitable for deriving absolute, generalizable findings, they serve as input for potential future hypotheses. The question "What is currently preventing you from making your energy consumption more sustainable?" allowed participants to let us know about hurdles in their everyday life to live more sustainably. 25.3% of the participants indicated that their energy consumption is already sustainable, while for 23.6% of the participants high investment costs (e.g., smart machines, smart meters) are a hurdle. In addition, 11.3% stated that missing knowledge about ways to reduce energy and the lack of transparency on one's energy consumption are a hindrance. The same share of people made their habits and comfort responsible for living more sustainably. Lastly, little flexibility for implementing energy efficiency measures due to rental agreements hinders 19.0%, and time and effort are a reason for 9.0%. The second question "Do you perceive your interest in energy-saving behaviour as constant or is it influenced by current political events?" aimed at the political interest of users in correlation with their energy consumption behaviour. 55.6% of the people stated that their energy consumption is dependent on current political events, whereas the rest stated it to be constant.

5 Discussion

This study examines an integration of individual and technological factors that influence the acceptance of smart energy apps in private households by building on UTAUT 2 and the model of subjective beliefs and investigating additional (relevant) variables that focus on the individual capabilities of potential users, namely personal innovativeness, digital literacy, perceived data privacy, and political interest (Venkatesh *et al.*, 2003; Abrahão, Moriguchi and Andrade, 2016; Girod, Mayer and Nägele, 2017; Sindermann, Kannen and Montag, 2022). Our results have several implications for both theory and practice. First, in terms of theoretical implications, we contextualize a model of technology acceptance in the context of smart energy apps. Generally speaking, such contextualization a) offers proof that the underlying general model (in our case UTAUT 2) is valid also in the domain investigated here, and b) offers opportunities for drawing inferences from the specific model about potential extensions to other domains (Hong *et al.*, 2014). Starting with the technological factors, surprisingly, we find no support in our data for the hypothesis that digital literacy or privacy concerns impact adoption intentions. In the case of digital literacy, this might stem from the experience that app developers provide intuitive applications usable by people with all levels of digital literacy. In the case of privacy concerns, however, our results contradict prior findings of Attour et al. (2020), giving rise to the question whether people generally get weary of data protection topics given its prominence in the online world. While this is good for technology adoption endeavours, this findings spark the debate of how to increase privacy attention in areas where risks are especially high for users (Pitkänen and Tuunainen, 2012).

While adoption research in other domains has demonstrated the relevance of individual characteristics, smart energy app research so far has not (He and Veronesi, 2017). Therein, the positive effects of personal innovativeness and environmental norms strengthen our call to take a socio-technical perspective integrating both individual as well as technical factors. In showing the effects of environmental norms, we expand the findings of Attour *et al.* (2020), who presented environmental concerns as factors impacting the frequency of use of smart energy apps, but not yet the intention to use. Adding to Yew *et al*. (2022), who present altruistic traits and the presence of children in households as relevant factors for predicting smart energy app adoption, our study highlights the role of individual characteristics such as personality traits and beliefs for adoption intentions. As our results show personal innovativeness as one relevant personality trait, the importance of future research to also assess other personality traits becomes evident. In addition, the non-significance of hedonic motivation could be either explained by users purposefully using the app to save costs, not to have fun, or by their inability to assess the fun factor with an app that is not yet on the market. Both explanations point at the necessity to find new incentives beyond increasing the fun factor in such contexts in order to drive adoption.

Referring back to the general purpose of contextualized models (Hong *et al.*, 2014), our study sparks discussion on which contextual moderators impact the role of personality traits for adoption intentions. In our study, the moderators age and gender play a significant role. The intention to use the app is 5.4% higher for male participants, which supports the findings of previous scholar on the topic of the digital divide stating that, on average, men are technically more (Perifanou and Economides, 2020). However, our findings refute digital divide findings of previous scholars in the context of age. In contrast to the findings of higher computer anxiety and technophobia in higher age groups, the oldest age group between age 50-71 showed significantly high behavioural intentions in our study (Elena-Bucea *et al.*, 2021). As a consequence, our results underscore the need for research to engage in detecting the determinants of IS contexts that impact whether age plays a role for adoption decisions in order to adequately address concerns regarding the digital divide (Perifanou and Economides, 2020).

Second, our research also offers a first pointer on the levers of IS for fostering the adoption of smart energy apps to ultimately create energy-saving behaviour in private households. The key barriers to reducing energy consumption mentioned in the open-ended question refer to facilitating conditions (monetary constraints, lacking smart home appliances), individual characteristics (lacking knowledge and transparency on energy consumption and reduction opportunities), and habits. While IS cannot solve monetary constraints, they do bear the affordances for creating more transparency through real-time information and recommendations as well as changing habits through positive nudging (Allen, Karanasios and Norman, 2014; Berger, Greinacher and Wolf, 2022). So, while our study presents an integrated model of the individual and technologic factors impacting the behavioural intentions of smart energy apps, it also offers a first understanding of barriers to adoption that are addressable through IS.

For practice, our results indicate which factors are important to consider when trying to increase adoption rates. As discussed, to increase behavioural intentions to use the app, app designers should focus on the environmental benefits to leverage environmental norms and address personal innovativeness. This could be implemented by focusing on the sense-making of energy use data through tangible examples and the visualization of negative effects of one's energy consumption. In terms of personal innovativeness, apps should be designed to spark the curiosity of users, for example through modern graphic layouts (Berger, Greinacher and Wolf, 2022). For policymakers and housing associations, the strong impact of facilitating conditions and monetary concerns in the open question is critical. Unlike apps that are stand-alone technologies, smart energy apps rely on the availability of smart phones, smart household appliances, and the appropriate technical infrastructure to measure energy consumption in real-time. The cost of developing this data infrastructure (e.g., smart meters, databases, sensors) and purchasing smart home appliances is often seen as a hindrance to transforming energy consumption in a more sustainable way. Therein, there is not just one construct "price" to consider in this context, but different costly components with different possibilities regarding which stakeholder groups finance which component. To tackle this problem, policymakers should carefully consider subsidies and other policy instruments that enable the transformation also for those less affluent.

As any other research, our study is subject to some limitations, which we address in the following. As mentioned in the beginning, smart energy apps are not yet widespread in households, making the measurement of actual use behaviour infeasible. The conversion rate of people actually using the app is a critical success factor for smart energy app adoption and should thus be assessed at a later point. Likewise, the impact of habits and costs on people's intention to use app are an interesting research pathway, as is an assessment of possible interactions between the variables. Additionally, this survey is based on screenshots and information given to the participants, instead of them actually using the app. This potentially provokes partly speculative answers in some of the constructs. To expand our analysis, a prototype app or mock-up could be used in future research. Furthermore, some of the constructs (e.g., political interest, environmental and social norms) are impacted by the culture and political environment one lives in, making our model somewhat specific to Germany. Therefore, we suggest implementing the study in other countries and potentially consciously assessing cultural moderators. Lastly, the key idea of our study is to understand the adoption of smart energy apps not solely depending on the technology-specific circumstances but as a factor impacted also by personal capabilities and attitudes in fields such as environmentalism or politics. Although the construct political interest was statistically not significant in our research model, many participants mentioned political reasons for energy consumption decisions in the open question of the survey. This controversial finding inspires the development of more extensive survey scales for the variable political interest, to gain deeper insights into the importance of this factor.

6 Conclusion

Raising awareness among householders about their energy consumption is a critical factor to reach climate neutrality in the building sector by 2050. Smart energy apps support this aim and help transform the building sector by focusing on its habitants. A smart energy app makes energy consumption visible and relatable, giving consumers the possibility to develop habits towards sustainable energy consumption and saving energy. To drive their adoption, this study developed and evaluated a technology acceptance model with a survey of 300 participants. Individual capabilities and personality traits such as personal innovativeness and environmental norms emerged as central factors driving behavioural intentions in contexts that are neither connected to involuntariness nor to hedonic motivation. To reach climate neutrality in time, the levers of IS play a critical role. While there are still many untapped opportunities of IS for sustainability, smart energy apps are one small component with the potential to make a positive environmental contribution.

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