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Abstract

Although smart energy technologies (SETs) can fulfill multiple tasks in increasingly decarbonized and digitalized energy systems, market diffusion is still limited. This study investigates which beliefs influence consumers' intention to adopt two smart-energy offerings, whether the rapid growth of the smart home market will now drive SET adoption, and if consumer-driven diffusion will lead to sustainability potentials being realized. Building on UTAUT2, a new theoretical model is proposed, and a consumer acceptance survey was conducted in Germany (n=700). Results indicate that a growing smart home market will not increase SET adoption and that "adjustable green defaults" should be introduced.

Keywords

adoption of innovation – smart energy – UTAUT2 – market diffusion – home energy management

Highlights

- New, extended UTAUT2 model to investigate adoption of smart energy technologies (SET).
- Survey (n = 700) to investigate beliefs influencing intention to adopt different smart energy offerings.
- Influences differ across the two smart energy offerings (smart meter, smart thermostat).
- Results suggest that the smart home market will not drive SET adoption and adjustable green defaults should be introduced.
- Implications for policymakers, market actors and future research are further examined

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1. Introduction

The transformation towards decarbonized energy systems poses challenges and offers new opportunities for energy providers, network operators, regulators, and new market actors. In countries with highly advanced energy systems, a critical project for all stakeholders is the digitalization of energy infrastructures. Digitalization is a central building block for integrating volatile renewable energy production into energy systems and markets (Hall and Foxon, 2014; Xenias et al., 2015). In addition to their relevance for smart-grid management, smart energy technologies (SET) can also play a crucial role for households.

On the one hand, they can reduce final energy consumption. Reducing final energy consumption is an integral part of states' decarbonization efforts (e.g., Directive 2012/27/EU, Article 3). Smart thermostats, for example, can reduce end users' final energy consumption directly (Wang et al., 2020; Schäuble et al., 2020). Smart meters can help reduce energy consumption indirectly by providing feedback (Berry et al., 2017; Gans et al., 2013; see Ford et al., 2017, p. 544, for a review of relevant studies). On the other hand, smart meters can also integrate households into the smart grid to increase demand-side flexibility (Parag and Butbul, 2018, p. 177). Thereby, the utilization of renewable power plants can be increased, supporting a cost-efficient transformation of energy systems (Wohlfarth et al., 2020). For electric utilities and new market actors, SETs offer opportunities for smart energy business models and innovation, such as data-driven rate models (Chasin et al., 2020; Venkatraman et al., 2021). However, will consumer-driven diffusion lead to these potentials being realized?

Market diffusion of smart energy devices is still at a low level (Statista, 2020, p. 163) and lags behind expectations (Sanguinetti et al., 2018a). In order to understand what will drive smart energy adoption in households and how to increase smart energy diffusion strategically, initial acceptance models have been developed and tested (Ahn et al., 2016; Chen et al., 2017; Gimpel et al., 2020; Girod et al., 2017). Although offering theoretical and empirical insights, some key questions have been left unaddressed.

First, household SETs can be understood as part of a broader smart home market that includes a wide range of non-energy benefits, services and promises (Furszyfer Del Rio et al., 2020; Sovacool and Furszyfer Del Rio, 2020; Strengers and Nicholls, 2017). The smart home market is growing rapidly, but will it also drive smart energy diffusion (Sovacool and Furszyfer Del Rio, 2020)? More specifically, will consumers' affinity for non-energy smart home benefits influence their intention to adopt smart energy offerings? The answer to these questions has consequences both for decarbonization efforts and for strategically increasing market diffusion of SETs. Smart home devices can potentially be detrimental to energy conservation (Hargreaves et al., 2018; Tirado Herrero et al., 2018) and other social goals by increasing energy demand (Nicholls et al., 2020, p. 1). Therefore, understanding the influence of consumers' affinity for non-energy smart home benefits on their intention to adopt SETs will indicate if the rapid growth of the smart home market will support energy conservation or if it will lead to increased energy consumption instead (cf. Sanguinetti et al., 2018b, p. 1897).

Second, initial acceptance models have not examined the relative importance of beliefs across the intention to adopt different SETs (cf. Gimpel et al., 2020, p. 8; Girod et al., 2017, p. 424). Instead, studies explain the intention to adopt or use one particular type of SET (cf. Gimpel et al., 2020).

Third, the literature on diffusion theory has established the fundamental insight that, at an early stage of diffusion, information on the advantages and disadvantages of new technologies is sought in the social environment (Rogers, 2003, p. 175; cf. Vrain and Wilson, 2021). Contrastingly, initial acceptance studies did not find "*social influence*" to be a significant influence on the intention to use smart energy devices (Gimpel et al., 2020, p. 8; similarly Ahn et al., 2016, p. 88; and only marginal influence in Girod et al., 2017). These surprising results make it necessary to examine this aspect both theoretically and empirically, as it is a core feature of diffusion theory and marketing strategies.

In order to examine consumers' acceptance of smart energy offerings and to address the mentioned shortcomings, this study proposes an adjusted acceptance model for the adoption of smart energy offerings. The model builds on the Unified Theory of Acceptance and Use of Technology (UTAUT2; Venkatesh et al., 2012). In order to test the model and investigate how technology-specific and personal beliefs influence the intention to adopt two smart energy offerings, a survey was conducted in Germany (n=700). Germany has an advanced energy system and introduced a law for the digitalization of the energy system in 2016. Results from a comparative cross-country study from Sovacool et al. (2021, p. 15) indicate that this case study could provide relevant information for smart energy diffusion in countries with similar conditions; that is, for upper income, urbanized countries. However, fundamental preconditions should be met before SETs can even be considered viable for supporting decarbonization in the residential sector. Tetteh and Amponsah (2020, p. 158) conducted a literature review on smart homes in sub-Saharan Africa. They highlight the following preconditions for smart home technology to be a viable option: reliable energy, economic development for appropriate employment and income levels, technological advancement and technological literacy.

This case study follows a comparative approach. All respondents were presented with the same survey questions relating to either an ideal-typical smart thermostat or smart meter offering. This approach enables examining the relative importance of beliefs across the intention to adopt different SETs. Moreover, it allows a better understanding of the importance of specific technological features like automation and feedback for the diffusion of smart energy in households.

2. Theoretical models and the adoption of smart energy technologies

The theoretical model proposed in this study is based on seminal work by Venkatesh and colleagues. Venkatesh et al. (2003) developed the Unified Theory of Acceptance and Use of Technology (UTAUT). UTAUT was developed to explain computer and information technology acceptance and use in organizational contexts (Venkatesh et al., 2003, p. 426). At its core, the model assumes that technology-specific and personal beliefs can explain employees' intention to use new technologies. UTAUT was later extended for the context of consumer studies (UTAUT2, Venkatesh et al., 2012).

UTAUT2 has seven constructs theorized to influence behavioral intention: *performance expectancy*, *effort expectancy*, *social influence*, *facilitating conditions*, *hedonic motivation*, *price value*, and *habit* (Venkatesh et al., 2012, p. 160). UTAUT and UTAUT2 have been applied as baseline models in different contexts and for different technologies (Venkatesh et al., 2012, p. 158). Accordingly, UTAUT models have already been adapted and extended in the context of SETs as well. SETs are built on information technologies, and thus it is reasonable to adapt UTAUT2 for this context (see Girod et al., 2017, p. 417). Extended UTAUT2 models to explain the acceptance of SETs most often include some form of environmental beliefs (Ahn et al., 2016; Baudier et al., 2020; Gimpel et al., 2020; Girod et al., 2017).

However, previous studies on the acceptance and adoption of SETs have also drawn on other theories and models. For example, Chen et al. (2017, p. 94) propose a model based on the technology acceptance model (TAM, see Davis, 1989; Venkatesh and Davis, 2000) and the Sustainable Energy Technology Acceptance model (SETA, see Huijts et al., 2012). Marikyan et al. (2019a) combine the Task-Technology Fit (TTF) model with constructs from TAM to explain actual smart home users' acceptance of the technologies. Taken together, although previous studies show similarities in some respects, there is not a consensus on the one model best suited to explain consumers' intention to adopt SETs (Chen et al., 2017, p. 94).

3. Research model and purpose

The proposed model assumes that three contexts influence the intention to adopt smart energy offerings. Firstly, the offerings address private households and consumers. Accordingly, the UTAUT2 model serves as the baseline model. However, it will be argued that the construct *Social Influence* should be adjusted for smart energy offerings, and a new construct is proposed. Secondly, similarly to previous studies on SETs, environmental beliefs are theorized to be relevant due to the positive environmental effects that the technologies are expected to provide (Ahn et al., 2016; Baudier et al., 2020; Gimpel et al., 2020; Girod et al., 2017; Perri et al., 2020; Whittle et al., 2020). Thirdly, in distinction to previous studies, *Affinity for Smart Home Security* and *Affinity for Smart Home Health* products are theorized to influence the adoption of smart energy for households, and new constructs are proposed.

3.1 UTAUT2 as the baseline model

The proposed model includes four constructs from the UTAUT2 baseline model. The construct *Performance Expectancy* measures the extent to which people believe that the smart energy offering is helpful to them in everyday life. More precisely, the survey items capture expectations regarding usefulness, performance of important tasks, and helpfulness in managing everyday life more efficiently. They are adjusted for the context of private households but basically adopted from Venkatesh et al. (2003, p. 447). It is theorized that higher expectations regarding the performance of smart energy offerings positively influence the intention to adopt them.

Effort Expectancy and *Hedonic Motivation* were adopted similarly. *Effort Expectancy* measures the degree of ease associated with using the SET (cf. Venkatesh et al., 2003, p. 450). The survey items capture the extent to which people believe they can easily learn how to use it, how simple and understandable operating the technology is expected to be, and to what extent they expect to utilize its capabilities. It is theorized that the degree of ease associated with using the SET positively influences the intention to adopt it. *Hedonic Motivation* is defined by Venkatesh et al. (2012, p. 161) as "the fun or pleasure derived from using a technology". Accordingly, survey items measure the extent to which people associate fun and entertainment from using the offering. *Hedonic Motivation* is theorized to influence consumers' intention to adopt SETs positively.

However, three constructs from the original UTAUT2 model are not included in this study. First, Baudier et al. (2020) find that the construct *Facilitating Conditions* is not reliable in the context of smart homes (Cronbach's Alpha at 0.654) and exclude it from their model. Thus *Facilitating Conditions* was not included in this model as well. Secondly, previous studies find that *Price Value* has no significant influence on intention to adopt in the context of smart home energy technologies (Baudier et al., 2020, p. 13; Gimpel et al., 2020, p. 7; Girod et al., 2017). Accordingly, it was not included in this model. Lastly, the construct *Habit* was also excluded (UTAUT2, Venkatesh et al., 2012, p. 161). In UTAUT2, *Habit* refers to past use of the technology. In a model that aims at explaining the adoption of new technologies, as is the case for the present study, it is assumed that most respondents have not used the technology extensively – if at all (cf. Tamilmani et al., 2019). Accordingly, in a survey in the US by Raimi et al. (2016, p. 69), fewer than half of the respondents had heard of the term "smart meter", and 64% of participant-written definitions demonstrated no understanding of smart meter technology. Similarly, in this study, 49.4% of respondents state that they have not yet thought about smart home, and 6.7% even state that they have not heard of the term at all. Thus, *Habit* is not included in this study.

3.2 Social Influence in the context of smart energy

The construct *Social Influence* has been fundamentally adjusted for this study. Proposed by Venkatesh et al. (2012, p. 178) and adopted, for example, by Girod et al. (2017, p. 420) and Baudier et al. (2020, p. 15), it initially measures the extent to which people perceive that others close to them believe they *should* use a specific technology. In previous studies related to SETs, *social influence* is not a significant influence on intention to use (Baudier et al., 2020, p. 13; Gimpel et al., 2020, p. 8; similarly, Ahn et al., 2016, p. 88; and only marginal influence in Girod et al., 2017). This finding is theoretically plausible because household SET systems stand alone in the sense that they function well without the participation of other households or individuals. In contrast, information and communication technologies often depend on others (friends, colleagues, or communities) to use the technology, as is the case for social networks or messenger services. It is plausible that individuals would want others to use the technology in these instances. For smart thermostats or smart meters, this is hardly the case. Thus, in this study, it is assumed that other people and media outlets (the internet, television, newspapers) can arouse interest in the technologies and thereby exert social influence on individuals.

The *Social Influence* construct thus differs fundamentally compared to previous studies.

3.3 Environmentalism and smart energy

For this study, the UTAUT2 model is extended. As mentioned before, beliefs on the extent to which people consider themselves environmentally conscious is a potentially relevant context for SETs (cf. Whittle et al., 2020, pp. 2-3). Smart thermostats, as well as smart meters, are advertised to reduce energy consumption without compromising comfort. Thus, the construct *Environmentalism* proposed by Ahn et al. (2016, p. 86) is included in the model.

3.4 Non-energy benefits: Health and Security

Lastly, the constructs *Affinity for Smart Home Security* and *Affinity for Smart Home Health* devices are included. The survey items were newly developed for this study to measure the extent of a person's affinity for smart home health or security products. Affinity is defined as an "inherent attraction to or liking for a particular person, place, or thing, often based on some commonality" (APA Dictionary of Psychology, 2021). The survey items capture the extent to which people find the core functions and value propositions of technologies useful, helpful, important, and expect them to fulfill their value proposition. For example, with *Affinity for Smart Home Security*, core functions described include the ability to use a smartphone to check whether doors and windows are closed as well as generally making the home safer. The survey items of *Affinity for Smart Home Health* capture the affinity for immediate detection of falls with connected notification to emergency services and the detection of irregularities in sleep patterns of elderly relatives.

Accordingly, smart home technologies are not necessarily energy-related (Wilson et al., 2017). Sovacool and Furszyfer Del Rio (2020) recently found that 267 smart home technologies are commercially available in the UK, and they suggest a classification in 13 categories of household appliances, including the categories "health and wellness" as well as "safety and security". Smart home health benefits "include the ability to alert relatives or health professionals to emergency events, aiding health diagnosis, and enabling aggregate level health analytics" (Sovacool and Furszyfer Del Rio, 2020, p. 9; see also Vadillo Moreno et al., 2017). Due to ageing populations, experts expect increasing demand for smart health devices (Furszyfer Del Rio et al., 2020, p. 7). On the other hand, smart home security devices can notify the police of emergencies or enable consumers to check on the phone if a door or window opened at home (Balta-Ozkan et al., 2014, p. 74; Furszyfer Del Rio et al., 2020, p. 8; Sovacool and Furszyfer Del Rio, 2020, p. 9). Balta-Ozkan et al. (2014, p. 76) find in a survey that consumers showed great interest in non-energy smart home benefits, such as security and health (cf. Bhati et al., 2017).

Furthermore, initial studies point to the importance of non-energy benefits to early adopters of smart home energy applications. Based on a survey that distinguishes four consumer segments at different positions along the path to adopt smart home energy management applications, Sanguinetti et al. (2018a, p. 282) conclude that "The fact that Owners and/or the Persuaded were more likely than the Unfamiliar to perceive smart home benefits of comfort, convenience (making chores easier), health, security, and enjoyment, but *not* energy savings, cost savings, energy management, or environmental impact suggests that non-energy benefits are driving [home energy management] smart hardware adoption".

Similarly, Reichmann (2021) finds in a qualitative study of early adopters of SETs that smart home devices offering non-energy benefits were the initial driver for adoption, not energy-related benefits.

Can it thus be expected that non-energy smart home benefits will be a driver for majorities of consumers to adopt SETs as well? The answer to this question can provide important insights. It will point to whether a broader diffusion of SETs can be expected and provide indications of how the diffusion of SETs could be strategically developed.

Accordingly, as Sanguinetti et al. (2018a, p. 282) point out, if SETs are “being adopted and used mainly for non-energy benefits, energy-conserving and/or demand response default settings could be critical features to ensure energy benefits”. Secondly, SETs should then be part of more comprehensive smart home packages or at least be technically compatible with non-energy applications. If non-energy smart home benefits do not drive the diffusion of SET, it cannot be expected that SETs will necessarily benefit from the rapid growth (cf. Sovacool and Furszyfer Del Rio, 2020) of the smart home market. Furthermore, the factors driving SET adoption should be promoted explicitly to support the diffusion of technologies conserving energy.

4. Method

4.1 Sample

In order to test the research model, a professional survey company carried out an online survey. Respondents were split into two groups (“M1 Heating”: n=354; “M2 Meter”: n=346), with each group representative of the population in terms of the distribution of age (between 18 and 69) and gender in Germany (see table 1). The survey was conducted in the state of North Rhine-Westphalia (NRW) and with the German language. NRW is the state with the largest population in Germany. It has both very densely and also sparsely populated regions.

Table 1

Demographics of the sample (M1 and M2).

Variable	Characteristic	Sample	Germany (in 2019)[1]
Age	18–29	21%	20%
	30–39	17%	19%
	40–49	22%	18%
	50–59	21%	24%
	60–69	19%	18%
Gender	Female	49%	51%
	Male	51%	49%

[1] Own calculation based on Destatis (2020).

Table 2
Levels of education (M1 and M2).

Without school diploma	0.3%
Secondary education	42.4%
Middle school diploma	22%
Technical college or university entrance qualification	35%

4.2 Information on smart energy offerings

Based on a market screening of smart home offerings in Germany, two ideal-typical smart energy offerings were developed (Chasin et al., 2020). Participants were presented with information on either of the two following smart energy offerings prior to the questionnaire. The ideal-typical offering “smart heating” includes, amongst other things, the automated control of heating and windows, the learning of habits and preferences of the residents in order to adjust the heating accordingly, and control options via an app. The ideal-typical offering "smart meter", on the other hand, makes it possible, amongst other things, to determine electricity consumption in real time, to receive personalized advice on reducing electricity consumption via an app, and to have saved CO2 emissions displayed. Notably, the offerings differ not only with regard to the technology. The offering “smart heating”, on the one hand, is presented without highlighting potential environmental benefits. Although heat supply is a central factor of the CO_2 footprint of households (Dubois et al., 2019, p. 147), no reference was made to corresponding reduction potentials through smart heating. The offering “smart meter”, on the other hand, points to environmental benefits and contains aspects of gamification, as consumers’ can receive personalized advice. In both offerings, the compatibility with other smart home components, especially in the areas of safety and health, is pointed out.

4.3 Measures and Model

All survey items were measured with a 7-point Likert-type scale. The model includes eight latent variables. The latent variables *Performance Expectancy*, *Effort Expectancy*, *Hedonistic Motivation*, *Social Influence*, *Affinity for Smart Home Security*, *Affinity for Smart Home Health*, and *Environmentalism* are specified as exogenous variables. They are theorized to positively and significantly influence the endogenous variable *Intention to Adopt*.

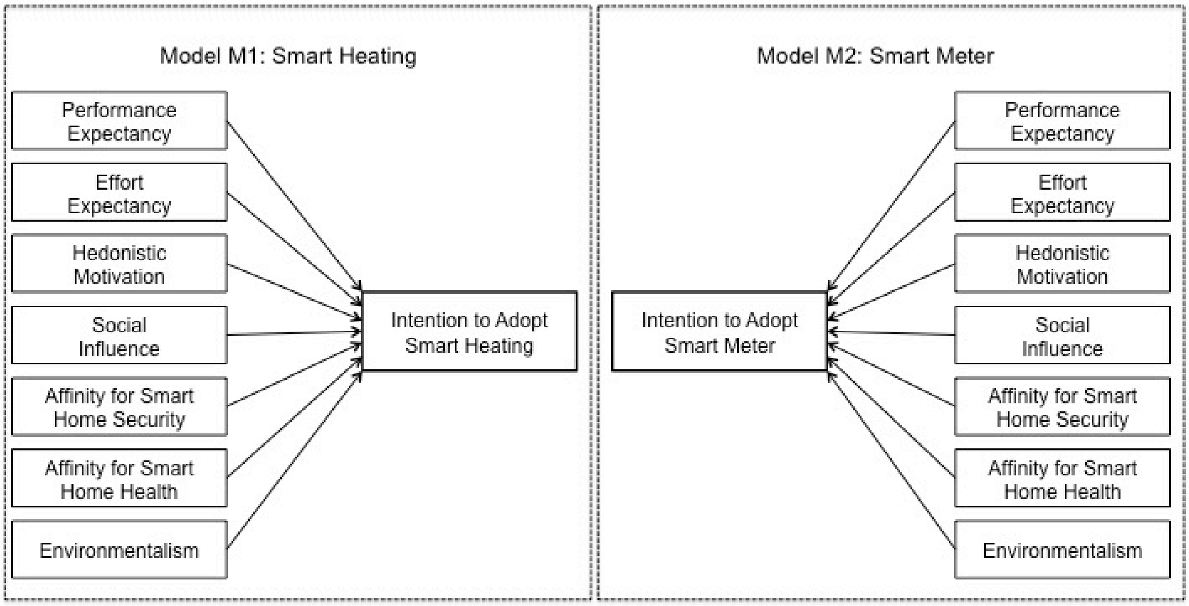

Fig. 1: The Proposed Comparative Research Model.

4.4 Initial model test and exclusion of items

The models were tested with R studio, and the package "lavaan" was used. In the absence of a multivariate normal distribution for the variables, an adjusted standard error estimate was defined with robust standard error estimates. Missing data were supplemented with the full information maximum likelihood method.

The test results show a good overall fit for the two initial measurement models, "M1 Heating" and "M2 Meter". Hair et al. (2014, p. 584) recommend the following cut-off values for models with more than 250 observations and twelve to thirty variables: a Comparative Fit Index (CFI) and Tucker-Lewis Index (TLI) value of greater than 0.92, Root Mean Square Error of Approximation (RMSEA) less than 0.07 and Standardized Root Mean Square Residual (SRMR) less than or equal to 0.08 (cf. Hu and Bentler, 1999). However, these are not absolute rules that can definitively determine a good or bad model fit but are intended to guide interpretation (Hair, 2014, p. 584).

Accordingly, although all tests point to the initial models fitting just fine ("M1 Heating", e.g., with $\chi 2(296) = 560.188$, CFI = 0.96, TLI = 0.95, RMSEA = 0.05, SRMR = 0.04), the models were tested based on Saris et al. (2009) as well in order to detect misspecifications of parameters. The test includes expected parameter changes, the modification index, and the power of the modification index. Fixed parameters are defined as misspecified if the modification index is significant and the power is low; parameters are misspecified if the modification index is significant, the power is high, and the expected parameter change is greater than the target expected parameter change. All 540 defined relations and non-relations of each model were investigated. Based on the test, seven identical survey items from models "M1 Heating" and "M2 Meter" were excluded (for a similar procedure, see Ahn et al., 2016, p. 87). One item each from *Hedonic Motivation*, *Security* and *Health,* and two items from *Social Influence* and *Environmentalism* were excluded.

Importantly, the latent variables *Security*, *Health*, and *Social Influence* were newly developed for this study and have not been tested before. Additionally, Ahn et al. (2016) originally proposed six items to measure *Environmentalism* but excluded two items because of their test results. This study initially adopted the six items proposed to measure *Environmentalism,* but the tests confirm Ahn et al. (2016) in that the two items should be excluded.

5. Results

5.1 Descriptive results

Descriptive results suggest that the intention to adopt both SETs is relatively low (see Table 3). For example, while 14.7% show clear agreement that they plan to adopt the smart heating offer ("I agree completely" + "I agree"), 29.4% show clear disagreement ("I do not agree" + "I do not agree at all"). However, the clear agreement about planning to adopt the smart heating offer is higher than current levels of market diffusion in Germany. Statista (2020, p. 163) calculates the market diffusion rate of smart energy management devices at 10.2% in Germany (this includes smart thermostats *but not* smart meters)[2]. Additionally, 25.1% are neutral regarding their plans to adopt the smart heating offer in the future. Although the market potential is not yet exhausted, the results indicate an overall limited market potential.

Table 3

Descriptive Results. *Intention to Adopt.*

Smart Heating	*I agree completely*	*I agree*	*I tend to agree*	*Neutral*	*I rather disagree*	*I do not agree*	*I do not agree at all*
ItA1	12.1%	17.2%	19.8%	15.5%	7.1%	7.6%	16.1%
ItA2	5.4%	9.3%	13.0%	25.1%	9.9%	8.8%	20.6%
ItA3	5.9%	11.6%	16.4%	22.6%	9.6%	9.0%	18.4%
Smart Meter	*I agree completely*	*I agree*	*I tend to agree*	*Neutral*	*I rather disagree*	*I do not agree*	*I do not agree at all*
ItA1	13.3%	19.1%	23.4%	16.5%	8.4%	4.6%	10.7%
ItA2	5.8%	11.0%	14.7%	24.3%	9.5%	7.2%	13.3%
ItA3	9.2%	11.0%	17.1%	24.0%	11.6%	6.4%	12.4%

[2] This includes thermostats, radiator controls, air condition controls, Weather forecast services with connection to a broader smart home, Temperature/wind/humidity sensors – but *not* smart meter.

In contrast, descriptive results show a pronounced affinity for smart home health and smart home security devices with relatively little rejection, as the following table highlights. For example, 35.8% show clear agreement that they would find it important to make their home safer through smart home technologies (*AS3*, “I agree completely” + “I agree”), whereas 12.4% show clear disagreement (“I do not agree” + “I do not agree at all”). Similarly, 36% show clear agreement that they would find it important if falls at home were immediately detected by sensors and passed on to the emergency services (*AH1*, “I agree completely” + “I agree”). Only 12.7% show clear disagreement (“I do not agree” + “I do not agree at all”).

Table 4

Descriptive Results. Affinity for Smart Home Security and Health, ‘Top-3’ and ‘Bottom-3’.

Affinity for smart home security	*I agree completely*	*I agree*	*I tend to agree*	*I rather disagree*	*I do not agree*	*I do not agree at all*
AS1	22.0%	21.1%	21.7%	6%	4.3%	8.0%
AS3	15.1%	20.7%	22.9%	6.4%	4.3%	8.1%
Affinity for smart home health	*I agree completely*	*I agree*	*I tend to agree*	*I rather disagree*	*I do not agree*	*I do not agree at all*
AH1	18.0%	18.0%	22.6%	5.4%	5.3%	7.4%
AH3	16.6%	20.4%	23.0%	6.1%	4.3%	7.3%

5.1 Reliability and validity

The reliability of the measurements is satisfactory. Cronbach's alpha for model "M1 Heating" ranges from 0.77 (*Health*) to 0.95 (*Intention to adopt*) and for model "M2 Meter" from 0.80 (*Health*) and 0.95 (*Intention to adopt*). Accordingly, all measurements exceed the recommended threshold of 0.7 (Hair, 2014, p. 123). Similarly, composite reliability ranges between 0.78 (*Health*) and 0.95 (*Intention to adopt*) for "M1 Heating" and between 0.82 (*Health*) and 0.94 (*Intention to adopt*) for "M2 Meter". Therefore, the values are above the recommended threshold of 0.50 (Fornell and Larcker, 1981).

Both convergent validity and discriminant validity were checked to determine the validity of the latent variables. Factor loadings are above the recommended threshold of 0.7 (Fornell and Larcker, 1981), except for one item (*ENV3*) of the construct "*Environmentalism*" and only in model "M1 Heating". In model "M2 Meter", the same item has a factor loading of 0.78. Thus, it was decided not to exclude the item ENV3. In order to confirm discriminant validity, it is confirmed that the squared correlations between latent variables are lower than latent variables' average variance extracted for all variables in both models.

Table 5

Smart Heating: Composite Reliability, Factor Loading, and Average Variance Extracted.

	Mean	SD	Cronbach's α	Composite Reliability	Factor Loading	Average Variance Extracted
Performance Expectancy						
M1_PE1	5.1	1.6	0.92	0.93	0.91	0.81
M1_PE2	5.1	1.5			0.88	
M1_PE3	5.0	1.6			0.90	
Effort Expectancy						
M1_EE1	5.2	1.4	0.94	0.94	0.92	0.83
M1_EE2	5.2	1.3			0.88	
M1_EE3	5.1	1.4			0.93	
Hedonic Motivation						
M1_HM1	4.4	1.8	0.89	0.89	0.94	0.78
M1_HM3	4.1	1.7			0.85	
Intention to Adopt						
M1_ItA1	4.2	2.0	0.95	0.95	0.91	0.86
M1_ItA2	3.6	1.8			0.93	
M1_ItA3	3.7	1.9			0.94	
Social Influence						
M1_SI2	3.4	1.8	0.87	0.87	0.83	0.77
M1_SI3	3.9	1.9			0.91	
Affinity for Security						
M1_SEC1	5.0	1.8	0.84	0.85	0.85	0.74
M1_SEC3	4.6	1.8			0.87	
Affinity for Health						
M1_HEA1	4.8	1.7	0.77	0.78	0.78	0.64
M1_HEA3	4.9	1.8			0.82	
Environmentalism						
M1_ENV1	5.3	1.4	0.85	0.86	0.87	0.61
M1_ENV2	4.9	1.4			0.82	
M1_ENV4	5.1	1.6			0.65	
M1_ENV5	5.1	1.3			0.78	

Table 6

Smart Meter: Composite Reliability, Factor Loading, and Average Variance Extracted.

	Mean	SD	Cronbach's α	Composite Reliability	Factor Loading	Average Variance Extracted
Performance Expectancy						
M2_PE1	5.2	1.5	0.91	0.92	0.93	0.79
M2_PE2	5.2	1.4			0.84	
M2_PE3	5.1	1.6			0.90	
Effort Expectancy						
M2_EE1	5.3	1.4	0.94	0.94	0.93	0.83
M2_EE2	5.2	1.4			0.91	
M2_EE3	5.1	1.4			0.90	
Hedonic Motivation						
M2_HM1	4.6	1.8	0.90	0.92	0.94	0.82
M2_HM3	4.3	1.7			0.85	
Intention to Adopt						
M2_ItA1	4.5	1.8	0.95	0.94	0.91	0.83
M2_ItA2	3.9	1.8			0.92	
M2_ItA3	4.1	1.8			0.90	
Social Influence						
M2_SI2	3.5	1.8	0.83	0.83	0.83	0.72
M2_SI3	4.0	1.9			0.91	
Security						
M2_SEC1	4.9	1.8	0.84	0.85	0.85	0.74
M2_SEC3	4.9	1.7			0.87	
Health						
M2_HEA1	4.8	1.7	0.80	0.82	0.84	0.69
M2_HEA3	4.7	1.7			0.82	
Environmentalism						
M2_ENV1	5.3	1.3	0.86	0.86	0.72	0.62
M2_ENV2	5.9	1.4			0.86	
M2_ENV4	5.2	1.6			0.78	
M2_ENV5	5.1	1.3			0.77	

5.2 Structural model results

The test results indicate good overall fit for both final measurement models. “M1 Heating”: $\chi2(161)$=260.972, $\chi2/df$=1.6, CFI=0.98, TLI=0.97, RMSEA=0.042 (with a 90% confidence interval of 0.034–0.05), SRMR=0.036, R^2 = 0.819. “M2 Meter”: $\chi2(161)$=257.590, $\chi2/df$=1.6, CFI=0.98, TLI=0.97, RMSEA=0.042 (with a 90% confidence interval of 0.033–0.05), SRMR=0.028, R^2 = 0.859.

5.3 Effects on the intention to adopt

The results differ regarding influences on *Intention to Adopt*. The intention to adopt the smart thermostat is significantly and positively influenced by *Performance Expectancy* (β = 0.215, p=0.013) and *Social Influence* (β = 0.452, p=0.000). Using f^2 to evaluate effect size, the effect of *Performancy Expectancy* on *Intention to Adopt* is small at 0.07, and the effect of Social Influence on *Intention to Adopt* is medium at 0.24. On the other hand, *Hedonic Motivation* (β = 0.496, p=0.002), *Social Influence* (β = 0.387, p=0.003) and *Environmentalism* (β = 0.094, p=0.012) significantly and positively influence the intention to adopt the smart meter. Both *Hedonic Motivation* and *Social Influence* show medium effect sizes with f^2 at 0.19 and 0.29, respectively. *Environmentalism* shows a small effect size at 0.05.

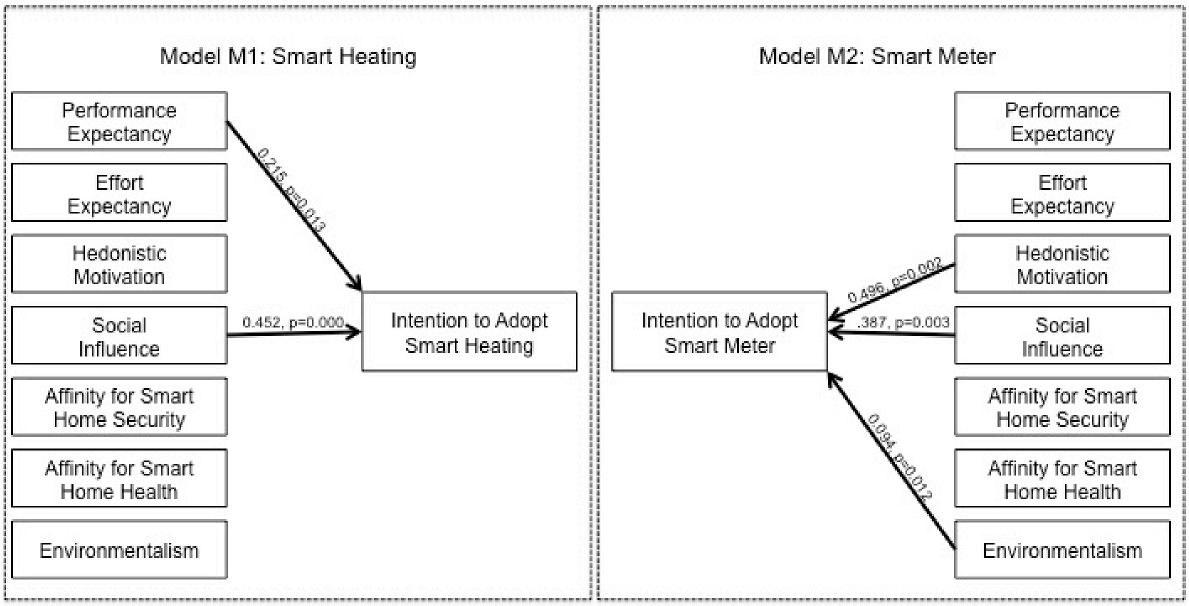

Fig. 2: Proposed Research Model and Influences on *Intention to Adopt*.

6. Discussion

The two overarching questions of this study are, firstly, what will drive smart energy adoption in households and, secondly, to what extent consumer-driven diffusion could lead to sustainability potentials being realized. The following discussion will take up these questions. It is structured along the main topics of this study. For each key topic, the results are compared with previous studies, highlighting differences, potentials for improvements and future research.

Moreover, results are discussed regarding whether and how the sustainability potential of the smart energy offerings can be realized and how diffusion can be accelerated. Implications are derived for different actors that play a role in the respective contexts. Finally, the limitations of this study and pathways for future research are discussed and outlined.

6.1 The role of automation and feedback: influences across smart energy technologies

Comparing the influences of technology-specific and personal beliefs on the intention to adopt across different smart energy offerings could allow for a more differentiated understanding of what drives acceptance and adoption of SETs (Girod et al., 2017, p. 424). This study confirms the assumption that the relative importance of technology-specific and personal beliefs differs across smart energy offerings.

More specifically, while the intention to adopt the smart thermostat is positively and significantly influenced by *Performance Expectancy* but not by *Hedonic Motivation*, results for the smart meter are the opposite in this regard. The result that *Performance Expectancy* significantly influences the intention to adopt the smart thermostat is in line with previous studies investigating the intention to adopt smart thermostats (Ahn et al., 2016, p. 88; Girod et al., 2017), including the comparable construct *Perceived Usefulness* (cf. Gimpel et al., 2020, p. 7). *Hedonic Motivation*, however, has no significant influence on the intention to adopt the smart thermostat. At first sight, the result contradicts previous studies related to smart thermostats, which find *Hedonic Motivation* a significant influence (Ahn et al., 2016; Girod et al., 2017; cf. also Gimpel et al., 2020, p. 6). However, the different results may be explained by the differences in the level of interaction provided by the devices. Ahn et al. (2016, p. 86) described a smart thermostat to respondents that "can also control, monitor and analyze energy use". The smart thermostat in this study offers high levels of automation and no feedback. Regarding levels of automation and feedback, the description of a smart thermostat in Ahn et al. (2016, p. 86) is thus more comparable with the smart meter described in the present study than with the smart thermostat. Accordingly, *Hedonic Motivation* positively and significantly influences the intention to adopt the smart meter.

These results indicate that the levels of automation and interaction could be relevant characteristics for the diffusion of SETs. More specifically, the results suggest that *Performance Expectancy* is a relevant influence in the context of a smart energy device allowing for a high level of automation, while *Hedonic Motivation* is a relevant influence in the context of smart energy devices allowing for a high level of interaction. Automation and interaction are discussed as the two key promises of smart home devices. Strengers et al. (2020) explain that "most smart home literature assumes that lifestyle expectations emerge from households themselves, and must either be 1) made more efficient through automation, or 2) supported through interaction design for better user experience".

Thus, the conclusion of this study regarding automation and interaction could be relevant not only for the diffusion of smart meters and smart thermostats but also for other emerging SETs in the smart home context. For example, especially the diffusion of electric vehicles (EVs) has vast potential to complement intermittent renewable energies *if* their charging patterns support stabilizing the grid by offering storage as well as flexible demand options (Boström et al. 2021). Wall boxes with smart charging software can be advertised and designed to allow for different levels of automation and feedback.

They can be integrated into smart home energy management systems in order for optimized self-consumption (e.g. in combination with PV) or in order to participate in flexibility markets via “aggregators” (Poplavskaya and de Vries 2020). Thus, it is necessary to improve our understanding of how levels of automation and feedback influence the diffusion of smart energy offerings in households.

Moreover, it is helpful to understand how these preferences influence adoption and then translate to actual use. In the end, the actual use of these technologies will influence the extent to which their efficiency potentials are realized or if, on the contrary, they lead to increased consumption (cf. Nicholls et al., 2020, p. 1; Strengers et al. 2019). Additionally, Marikyan et al. (2019b, p 150) point out that exploring pre-adoption and postadoption perceptions will help in understanding the cognitive process of technology adoption, behavioural change, and subsequent diffusion in the mass market. This aspect seems to be especially relevant in the context of automation and interaction because each function can potentially improve efficiency, but they can also undermine the benefits of each other. Interactive devices might lower the efficiency potential through automation because user “inefficiencies” are more pronounced. Also, if a device provides high levels of automation but no interaction, users’ “needs” (e.g. perceived comfort) could undermine environmental benefits and increase consumption.

Implications: In order to accelerate the diffusion of SETs, energy utilities and new market actors offering smart energy products should thus design and market devices in such a way that easily allows users to choose between high levels of automation, high levels of interaction and feedback, or high levels of both. In a more elaborate proposal that also considers sustainability and user behavior, Sintov and Schultz (2017) argue for the development and introduction of “adjustable green defaults” for smart home technologies. The goal is to maximize energy efficiency and sustainability of smart home devices on the one hand, while on the other hand taking into account consumer preferences regarding automation and control in order to maximize adoption rates and default acceptance (Sintov and Schultz 2017, p. 9). Policymakers or consumer advocate groups could introduce product certificates based on “adjustable green default” criteria to ensure that consumer needs are met, efficiency improvements and consumption reductions are guaranteed, and diffusion is supported.

6.2 Sustainability and smart energy offerings

Early seminal studies on user perceptions of smart home technologies found that reducing energy use and protecting the environment were perceived as drivers for smart home technologies (Balta-Ozkan 2014, p. 1183; Wilson et al. 2017). Wilson et al. (2017, p. 76) conducted a national survey in the UK, finding that “survey respondents clearly perceive the *main purpose* of SHTs to be controlling energy, heating and appliances”. Similarly, Schill et al. (2019, p.182) find in a quantitative study in France that consumers’ level of *environmental concern* affects their willingness to purchase “eco-friendly smart home objects”.

This study and others on smart home and smart energy offerings indicate that environmental and sustainability attitudes *do not* play a significant role in smart home and smart energy diffusion.

Previous quantitative acceptance studies show no significant influence of environmental beliefs on the intention to adopt smart thermostats, despite the potential of the technology to reduce energy consumption (Ahn et al., 2016; Girod et al., 2017). This study confirms previous results regarding smart thermostats, as *Environmentalism* does not significantly influence the intention to adopt the smart thermostat offering. The results regarding the smart meter indicate that *Environmentalism* will not be a driving force for smart meter diffusion as well. Although *Environmentalism* positively and significantly influences the adoption of the smart meter, the effect is only marginal even though the offer includes green energy, personalized advice on how to reduce energy consumption, and displays how much CO_2 has been saved. Thus, people who consider themselves environmentally more conscious show only a marginally higher intention to adopt the smart meter offer presented. Relatedly, Perri et al. (2020) find that supporting environmental sustainability does not significantly influence the intention to adopt smart energy consumption behaviors.

Girod et al. (2017, p. 424), discussing the finding that environmental beliefs do not influence the adoption of smart thermostats, refer to assumptions in the literature that high environmental consciousness tends to be associated with post-materialistic worldviews. Accordingly, individuals with an image of themselves as environmentally aware are less likely to use new “green” technologies. Another reason could be that experts’ views on smart home technologies and market actors’ marketing strategies do not primarily revolve around sustainability and energy efficiency. Furszyfer Del Rio et al. (2021, p. 14) interviewed smart home experts in the UK and the US. They find that the majority of the experts perceive smart home technologies “as means to enhance comfort and convenience” instead of promoting resource conservation and efficiency. Accordingly, Furszyfer Del Rio et al. (2021, p. 14) note that this “may as well lead to unsustainable energy practices”. Similarly, Strengers et al. (2020) conducted a qualitative content analysis of online, magazine and trade articles about the 21st Century smart home. They conclude that devices are often “primarily marketed as a way to deliver a range of home improvements, with energy reduction being a secondary consideration or side-benefit”.

Implications: The different results highlight the rather complicated relationship between sustainability and smart home technologies (cf. Nicholls et al. 2020; Sovacool et al. 2021, pp. 2). Persons viewing themselves to a greater extent as environmental friendly do not necessarily show higher intentions to adopt smart energy offerings. In general, however, people perceive enabling energy efficiency and environmental conservation as a central purpose of smart homes. For market actors offering smart energy devices, the results of the different studies indicate that advertising should relate to environmental concerns and smart energy as a solution to these concerns instead of creating an image of environmental-conscious residents using smart thermostats. However, to provide empirical evidence for this hypothesis, market actors like utility companies or new market actors should conduct market studies comparing consumers’ receptiveness towards the two different sustainability-centred advertisements and in different cultural contexts (cf. Furszyfer Del Rio et al. 2021).

6.3 Why Social Influence is relevant

Social Influence has a highly significant effect on the intention to adopt both SETs ($p<0.01$). In this study, *Social Influence* measures the extent to which other people or the media arouse a person's interest in a smart home. As discussed in section 3.2, the construct thus departs from previous studies based on the UTAUT2 model of Venkatesh et al. (2012, p. 178; see Baudier et al., 2020; Girod et al., 2017; similarly Ahn et al., 2016) because previous studies measure the extent to which people believe that others close to them believe they *should* use the technology. The divergent construction of *Social Influence* may explain why significant influence on the intention to adopt is found in the present study, whereas no significant influence is found in previous studies of SETs (Baudier et al., 2020, p. 13; Gimpel et al., 2020, p. 8; similar to Ahn et al., 2016, p. 88; and only marginal influence in Girod et al., 2017).

In this study, *Social Influence* is the only technology-specific belief that positively and significantly influences the intention to adopt *both* smart energy offerings, highlighting its importance for market diffusion even more. Moreover, the finding corresponds to Rogers (2003, p. 175) regarding the role of information in innovation diffusion (cf. Vrain and Wilson, 2021). Thus, in contrast to previous studies, this study clarifies that the social environment is also highly relevant for the diffusion of SETs in households. Market actors aiming at increasing market diffusion of smart energy in households could thus base their marketing or diffusion strategies on this well-established insight.

6.4 The influence of non-energy smart home benefits

The affinity for non-energy smart home health and security benefits is theorized to influence the intention to adopt either smart energy offering. Initial studies suggest that non-energy benefits drive the early adoption of smart home energy devices (Sanguinetti et al., 2018a see also Reichmann 2021). In case this assumption holds, accelerated diffusion of smart energy devices can be expected, driven by the growth of the general smart home market. Descriptive results show a pronounced affinity for smart home health and smart home security with relatively little rejection (see section 5.1, Table 4). These descriptive results correspond with expectations for robust market growth. Statista (2020, p. 87), for example, expects annual revenue growth rates of 17.2% in the global smart home security segment until 2024 (from 15.9 billion US$ in 2019 to 35.3 billion US$ in 2024; cf. Sovacool and Furszyfer Del Rio, 2020).

However, the affinity for smart home health and smart home security devices does not significantly and positively influence the intention to adopt the smart thermostat or the smart meter offering. Respondents with a pronounced affinity for security or health devices do not show an increased intention to adopt either smart energy offering. These results suggest being cautious about assuming that a growing smart home market will accelerate the diffusion of energy-conserving devices. On the contrary, the market diffusion of smart home devices may lead to increased energy consumption. Similarly, Strengers et al. (2020), based on a qualitative content analysis of online, magazine and trade articles about the 21st Century smart home, find "pleasance" as a dominant, overarching, energy-intensive vision of smart home. Saving energy is defined as only one quality of "pleasance", with other qualities (like "aesthetic experience", "convenience and simplicity") undermining more sustainable ways of living. Additionally, they point out that smart thermostats may "promote interactions which may increase energy use" in order to provide comfort and "pleasance". Jensen et al. (2018, p. 10) find such an "energy paradox" with conflicting desires in another qualitative study of users of smart homes.

Implications: According to recent studies, sustainability does not appear to be a central issue for consumers, experts and marketing strategies regarding smart homes. This study investigates the direct influence of the affinity for two key smart home services (security and health) on the intention to adopt smart energy devices. The results of this case study thus empirically substantiate raised concerns that a growing smart home market will not accelerate the diffusion of energy-conserving devices. On the contrary, the market diffusion of smart home devices may lead to increased energy consumption. Furszyfer del Rio et al. (2021, p.15) urge that "technologies are designed and manufactured with consideration of not just economics, but also the social and environmental impacts of their use". Strengers et al. (2020) argue even, that a disruption of the dominant vision of smart homes might be necessary.

Following this line of thought, SETs could be envisioned as a solution to the climate crisis and as stand-alone devices, decoupled from the broader smart home market and its dominant vision of "pleasance". Energy utilities and new market actors that aim at supporting decarbonization and limiting climate change thus have to ensure that the diffusion of their products improves sustainability and does not increase consumption (cf. Sintov and Schultz 2017). Consequently, policymakers cannot expect that the diffusion and market growth of smart homes will lead to the diffusion of smart energy devices and reduced energy consumption. If smart energy in the residential sector is considered a building block for the energy transition, the results of this case study indicate that policymakers need to actively govern this segment and make sure that smart energy contributes to decarbonization goals. This objective could be achieved by introducing certificates for smart home products that meet the criteria of "adjustable green defaults" (see section 6.1) or by introducing product standards, limiting the diffusion of those devices that do not ensure energy efficiency and reduced consumption.

6.5 Limitations and future research

This study has several methodological and content-related limitations that should be considered. The limitations point to pathways for future research. *First*, the most relevant limitation of this study is that it was conducted only in Germany, in the state of North Rhine-Westphalia (NRW). Previous quantitative adoption studies were each also conducted in a single country and not across different countries and cultural regions (cf. Ahn et al. 2016; Baudier et al. 2020; Chen et al. 2017; Girod et al. 2017; Marykian 2019a), pointing to substantial limitations of this strand of literature including this case study. Some cross-country and cross-cultural differences have been investigated, based on other research methods (e.g. Balta-Ozkan 2014). Furszyfer del Rio et al. (2021) examine how cultural factors might shape the diffusion and use of smart home technologies. They conducted original expert interviews and media content analysis in four upper-income, urbanized countries based on a mixed-method approach. Although Furszyfer del Rio et al. (2021, p. 158) conclude that "across cultures, SHT adoption is currently driven by the personal comfort and lifestyle benefits", pointing to similarities regarding adoption across comparable countries, a nuanced discussion is required to enable policymakers and market actors to make evidence-based decisions. Future quantitative studies should include different countries. As the test results of this case study show a good overall fit for both final measurement models, the model could be applied in the context of different countries and cultural regions. This approach would allow a better understanding of the relevance of cultural differences on the intention to adopt smart energy offerings. Importantly, it could substantiate the results of this case study.

Second, this case study indicates that influences on the intention to adopt differ across the two smart energy offerings. Its results indicate that levels of automation and interaction are relevant for the diffusion of smart energy offerings, and further research is needed to substantiate this finding. Future studies, presenting the same SETs to respondents but describing them with different levels of automation and interaction are necessary to verify these findings. Researchers should compare influences across other emerging smart energy offerings that provide flexibility, such as EV charging management devices and heat pumps (cf. Sovacool et al. 2021, p. 2).

Third, this study did not explore and discuss questions of social exclusivity. Several aspects of SETs could pose fundamental barriers for different social groups and income levels, even in upper-income countries. More specifically, Balta-Ozkan et al. (2013, p. 372) highlighted concerns of exclusivity "for those on low incomes (lack of financial means), the elderly (due to computer illiteracy and long waiting times to recoup costs) as well as people living in older properties (lack of their compatibility to install smart technologies)", possibly pointing to "increasing social divisions" in the short to medium terms. Moreover, Shirani et al. (2020) examined perceptions of smart technology amongst "vulnerable consumers", with the latter questioning how the technologies would improve everyday lives and energy use, showing skepticism and concerns regarding possible increased energy consumption. Policymakers should strongly consider these aspects of exclusivity and added value for different income and social groups (see the discussion in Shirani et al., 2020, pp. 7). These concerns will be even more relevant with the diffusion of the expensive smart energy devices used with EVs and heat pumps.

7. Conclusion

The market diffusion of SETs in households is still at a nascent stage. Thus, this study investigates the influence of technology-specific and personal beliefs on consumers' intentions to adopt a smart thermostat *or* a smart meter offering in Germany. Results confirm, *firstly*, the hypothesis that the relative importance of technology-specific and personal beliefs differ across smart energy offerings. The intention to adopt a smart thermostat is significantly and positively influenced by *Performance Expectancy* and *Social Influence,* whereas *Hedonic Motivation*, *Social Influence* and *Environmentalism* significantly and positively influence the intention to adopt a smart meter. Results indicate that the levels of automation and interaction could be relevant features of SETs influencing their market diffusion. More specifically, results suggest that *Performance Expectancy* is a relevant influence if SETs allow for a high level of automation. In contrast, *Hedonic Motivation* is a relevant influence in case SETs allow for a high level of interaction and feedback. In order to accelerate the diffusion of SETs, devices could thus be designed and advertised in a way that they easily allow users high levels of automation as well as high levels of interaction and feedback. Thereby, a broader segment of consumers intending to adopt smart energy will be reached. *Secondly*, in contrast to previous studies in the field, *Social Influence* has a highly significant and positive influence on the intention to adopt both SETs. In this study, theoretical reasons are given as to why the construct *Social Influence* should be adjusted for the context of SETs. Moreover, the study's empirical results correspond to the fundamental insight of Rogers (2003, p. 175) that, at an early stage of diffusion, information on the advantages and disadvantages of new technologies is sought in the social environment. Thus, these seminal insights should not be neglected when aiming to increase the diffusion of different SETs for households strategically. Instead, this study's results indicate that recognizing social influences should play a central role in diffusion efforts. Finally, a pronounced affinity for non-energy smart home security and health benefits does not increase the intention to adopt smart energy devices. Accordingly, it cannot be expected that the general growth of the smart home market will automatically accelerate the diffusion of SETs. Moreover, high affinity in the non-energy benefits contrasts with relatively low intentions to adopt the smart energy offerings.

If SETs in households are to be part of decarbonization strategies, several aspects would have to be addressed. *Firstly*, the results of this case study do not indicate a consumer-driven demand-pull diffusion. The technologies' broader diffusion would thus have to be supported by policies. *Secondly*, care must be taken to ensure that smart homes do not lead to increased consumption. The results of this study tend to suggest that increased energy consumption is to be expected. Adjustable green defaults should become the standard and, if necessary, be ensured through appropriate regulation to prevent the diffusion of smart homes and smart energy devices from leading to increased energy consumption.

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ANNEX

Latent Variables and Items

The final measurement model includes 21 items to measure eight latent variables.

Table 3
Latent Variables and Items.

Latent Variable	***Items***		**Sources**
Intention to Adopt	*ItA1*	*I can imagine using [it] in my household.*	Adapted from (Girod et al., 2017)
	ItA2	*I plan to use [it] in the future.*	
	ItA3	*I am sure I will use [it] in the future.*	
Performance Expectancy	*PE1*	*I would find [it] useful in everyday life.*	Adapted from (Venkatesh et al., 2003)
	PE2	*[It] can perform important tasks.*	
	PE3	*[It] helps to manage everyday life more efficiently.*	
Effort Expectancy	*EE1*	*I would find it easy to learn how to use [it].*	Adapted from (Venkatesh et al., 2003; Girod et al., 2017)
	EE2	*Operating [it] would be simple and understandable.*	
	EE3	*I would find it easy to learn how to utilize the capabilities of the smart home heating package.*	
Social Influence	*SI2*	*I want to look more deeply into smart homes because many people I know use smart home packages.*	New construct
	SI3	*Internet, television, newspaper or other media have piqued my interest in smart home packages.*	
Hedonic Motivation	*HM1*	*Using [it] would be fun for me.*	Adapted from (Venkatesh et al., 2012)
	HM3	*Using [it] would be very entertaining.*	
Affinity for Smart Home Security	*AS1*	*I would find it useful to be able to check whether all windows and doors are locked at all times via a smartphone.*	New construct

	AS3	*I would find it important to make my home safer through smart home technologies.*	
Affinity for Smart Home Health	*AH1*	*For me or my relatives, I would find it important if falls at home were immediately detected by sensors and passed on to the emergency services.*	New construct
	AH3	*I would find it a great help in caring for elderly relatives if sleep irregularities were detected and reported.*	
Environmentalism	*ENV1*	*It is important to me that the products I use do not damage the environment.*	Adapted from (Ahn et al., 2016)
	ENV2	*I consider the potential impact on the environment in many of my decisions.*	
	ENV4	*I am concerned about wasting the resources of our planet.*	
	ENV5	*I would like to describe myself as responsible for dealing with the environment.*	